Silver Spoons and Scales of Justice: The Fairness Preference over Unequal Intergenerational Wealth Transfers

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Abstract

Intergenerational transfers are widespread and significantly unequal. This study explores people's fairness preferences regarding inequality caused by wealth transfers from economically advantaged parents through a large-scale experiment. In the experiment, workers and their parents completed assignments. Workers' earnings were derived either from their own merit or luck, or from wealth transferred by their parents, also earned via merit or luck. Impartial spectators from the U.S. and China then made real distributive decisions. Our results indicate a pronounced aversion among Americans to inequalities stemming from intergenerational transfers compared with those from self-earned wealth. In contrast, the Chinese exhibited only a mild aversion. Moreover, Americans showed a preference for intergenerational meritocracy, more accepting inequalities in transferred wealth when it resulted from parental merit rather than parental luck—a preference not shared by the Chinese. Further experiments suggest that attitudes toward unequal intergenerational wealth transfers are primarily driven by whether parents possess wealth to transfer rather than the choice to transfer it.

JEL Classification: C90, D31, D63, D91

Keywords: Fairness, wealth inequality, social preference, intergenerational transfer

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1 Introduction

Intergenerational transfers, including inter-vivos gifts and inheritances, are widespread. In the U.S., the annual value of inheritances and inter-vivos transfers averaged approximately $350 billion (2016 dollars) from 1995 to 2016, matching the total personal savings recorded during the same period (Feiveson and Sabelhaus, 2018). However, these transfers are highly unequal. Wealthier parents pass on their economic advantage by giving substantially more to their adult children (Corak, 2013). In contrast, low-income parents often lack the means to provide and sometimes even rely on financial support from their children (Bowles and Gintis, 2002)[1]. Recent studies have found that inequality in intergenerational transfers contributes to overall inequality (Piketty, 2011, 2014; Elinder et al., 2018; Boserup et al., 2016; Black et al., 2022) and depress upward social mobility (Corak, 2013).

To what extent do people view it fair for wealthy parents to transfer significant wealth to their children? The answer to this question is crucial as it influences the design and public support of related policies, such as inheritance and gift taxes (Starmans et al., 2017; Cappelen et al., 2020). Consequently, implementing these redistributive tax policies further impacts the immediate and future dynamics of societal inequality (Nekoei and Seim, 2023). Additionally, perceptions of fairness directly affect individual welfare, potentially reducing effort and investment due to perceived unfairness (Bjørnskov et al., 2013).

Much of the existing literature focuses on fairness preferences over self-earned wealth inequality (see a recent review by Cappelen et al., 2020 and Trautmann, 2023). This body of work documents a consistent pattern of meritocratic fairness preference: inequalities arising from merit, such as performance and risk-taking, are perceived as more acceptable than those resulting from uncontrollable luck. We advance the literature by providing an incentivized experimental measurement of fairness preference over unequal intergenerational wealth transfers.

This paper aims to address two main questions. First, do people have a meritocracy fairness preference within intergenerational transfer? That is, are individ-

[1] Pew Research Center, January 2024, “Parents, Young Adult Children and the Transition to Adulthood”

uals more accepting of intergenerational inequality when parents have earned their wealth through merit rather than luck? While the existing literature documents a robust pattern of meritocracy fairness for self-earned wealth, whether this pattern persists in intergenerational inequality is not straightforward. From the older generation's viewpoint, there may be a strong argument for respecting parents' merit in wealth generation and their intentional wealth transfers to subsequent generations. In contrast, from the younger generation's perspective, such unequal transfers originate from the older generation and are largely beyond the children's control. Consequently, all forms of intergenerational transfers might be perceived similarly, regardless of how the wealth was earned.

Second, and perhaps more importantly, do people view inequality caused by wealth transfers from economically advantaged parents as fair as inequality from self-earned wealth? The existing studies on self-earned wealth are silent on this issue. However, anecdotal evidence suggests that people consider it unjustifiable for wealthy parents to continue shaping the economic futures of their descendants through such transfers. For example, Piketty et al. (2023) advocates for higher taxes on inherited wealth than on self-made wealth.

To address our research questions, we conducted a tightly controlled, incentivized experiment.[2] We recruited college students as "workers" to complete assignments, and one of their parents was also recruited to participate. Both students and parents participated concurrently from separate locations, with communication between them prohibited to ensure the independence of their decisions. We verified familial relationships by requiring parents to provide their child's college ID number and an official document, which we then cross-checked against the student's enrollment records. Importantly, we recruited a large and broadly representative sample from both the United States and China, each consisting of over 2,700 par-

[2] Answering these questions using field data presents significant challenges. First, fairness preferences for redistribution are not directly observed in the field. Empirical studies often rely on various proxies, such as support for redistribution policies (Roth and Wohlfart, 2018), yet factors like efficiency concerns and trust in government also shape support for these policies (Stantcheva, 2021). More fundamentally, field data often does not capture people's beliefs about the sources of inequality. Even when such beliefs are identified, isolating them in a ceteris paribus analysis is challenging due to confounding factors. For instance, it is commonly believed that individuals receiving large wealth transfers may exhibit lower work effort—a concept known as the *Carnegie Conjecture*.

ticipants, termed "spectators." These spectators were tasked with deciding how to redistribute initial earnings between two paired "workers."

The experiments began with four between-subject treatments: the luck treatment (L), the merit treatment (M), the luck-parent treatment (LP), and the merit-parent treatment (MP). The workers in each treatment completed the same assignment under the same incentive. The only difference was that their initial earnings were determined by different rules, which were not disclosed to the workers before or after the assignment.[3] In the L and M treatments, paired workers' initial earnings were independently determined by a random lottery or their performance, yielding 0 or 6 points. In the LP treatment, parents' earnings were determined by the lottery, with possible earnings of 0 or 15 points. Parents who earned 15 points were asked if they wished to transfer 6 points to their child. Parents were informed that this transfer would determine their child's final payment, although other factors could also play a role. Parents who earned no points were unable to make a transfer, and all transfer decisions were anonymous to their children. The MP treatment followed the same setup as LP, except that parents' earnings were based on their assignment performance.

Spectators were fully informed of the conditions under which the workers and their parents operated. We ensured that all workers, across treatments, were viewed identically by spectators, except for the rules determining their earnings. Given that the initial earnings of the paired workers were determined independently, one pair could have three different initial earning outcomes.[4] We employed a contingent response method to assess the spectators' fairness preferences, requiring them to make redistribution decisions among the workers for all possible earning outcomes. Our analysis, however, focuses primarily on scenarios where earning distribution was unequal, with one worker receiving 6 points and the other receiving none.

The LP and MP treatments reflect several critical elements of real-life intergenerational wealth transfers. First, the earnings of the younger generation are directly shaped by the decisions of their biological parents, underscoring the distinct and

[3] Workers only know their performance might determine their payoff, but other factors might play a role.

[4] One worker has 6 points, and another has 0 points; both have 6 points; or both have 0 points.

significant influence parents have over other relatives or friends (Rubin and Chung, 2013). Second, the inequality in wealth transfers often originates from economically advantaged parents who, after benefiting from their own earnings, choose to pass on their advantages through transfers. Third, it is ultimately the decision of wealthy parents whether to transfer a portion of their wealth to the next generation, highlighting the personal agency involved in these transfers.

Our primary contribution is presenting the first incentivized experimental evidence on fairness preferences regarding inequality caused by wealth transfers from economically advantaged parents. In the U.S. samples, we first confirm the prevailing meritocratic view of fairness, consistent with existing literature. Specifically, Americans were more inclined to accept unequal distributions in the M treatment compared to the L treatment. Second, evidence supports the notion of intergenerational meritocracy: Americans showed a greater willingness to accept unequal intergenerational transfers when parental earnings were the result of merit (MP treatment) rather than luck (LP treatment). Third, Americans view inequalities stemming from intergenerational transfers as highly unfair. For instance, they are less tolerant of inequality in the MP treatment compared to the M treatment. Similarly, they accept significantly less inequality in the LP treatment compared to the L treatment. In fact, the accepted inequality in the MP treatment is even marginally lower than in the L treatment.

The analysis of perceptions among adults in China yields different insights. First, while the Chinese, like their American counterparts, accept more inequalities that stem from merit rather than luck, the difference in inequality acceptance is much smaller. Second, we found no evidence supporting an intergenerational meritocratic fairness view in China, as the differences in inequality acceptance between MP and LP treatments were negligible. Third, our findings only weakly suggest that unequal intergenerational wealth transfers are viewed as unfair in China. Specifically, while the acceptance level of inequality in the MP treatment is lower than that in the M treatment, the differences are not robustly statistically significant. Moreover, the acceptance levels of inequality in LP treatment are comparable to those in L treatment.

The inequality observed in the MP and LP treatments stems from two sources:

(1) the disparity in parents having wealth available to transfer, and (2) the decision by some economically advantaged parents to transfer earnings while others choose not to. To understand which sources influence the aversion to unequal intergenerational wealth transfers, we introduced two additional treatments, MPN and LPN, where N stands for "no choice." These treatments mirror the MP and LP settings, except that the transfer is mandated. Once parents complete their assignments, they are informed that a portion of their earnings will be automatically transferred to their children. We find that the results from the MPN and LPN treatments are similar to those of the MP and LP treatments. Hence, people's attitudes toward unequal intergenerational wealth transfers are mainly driven by the fact that some parents have wealth to help their children while others do not.

What psychological mechanism underlies the aversion to inequality resulting from intergenerational wealth transfers, as opposed to self-earned wealth? One potential explanation is the negative perception of intergenerational mobility generated when economically advantaged parents continue to influence economic outcomes for future generations through wealth transfers. Alesina et al. (2018) discovered that the perception of low intergenerational mobility heightens support for redistribution in the U.S. and Europe. Another explanation is that individuals aggregate parental and children's earnings when redistributing transferred wealth to the younger generation. This could imply that people view the tax system for self-earned earnings as fundamentally unfair and seek to rectify this through more aggressive redistribution in cases of transferred wealth. However, further analysis does not support this conjecture.

Related Literature: Our paper contributes to the extensive research on fairness attitudes toward self-earned inequality. Much focus has been placed on the conditions under which inequality is perceived as more or less acceptable (Konow, 2000; Cherry et al., 2002; Falk et al., 2003; Alesina and Angeletos, 2005; Cappelen et al., 2007; Almås et al., 2010; Cappelen et al., 2010, 2013; Durante et al., 2014; Mollerstrom et al., 2015; Akbaş et al., 2019; Cassar and Klein, 2019; Almås et al., 2020; Andreoni et al., 2020; Cappelen et al., 2020; Fehr et al., 2021; Cappelen et al., 2022c,a; Trautmann and van de Kuilen, 2022; Bortolotti et al., 2023; Cappelen et al., 2023). These studies document that inequalities arising from risk-taking or superior performance are typically viewed as fairer than those stemming from sheer luck. Moreover, the circumstances and procedures under which people make their choices might also influence their perceptions of fairness (Schmidt and Trautmann, 2019; Dong et al., 2022; Trautmann, 2023; Andre, 2024). Within this body of literature, our experimental design aligns closely with that of Almås et al. (2020) and subsequent studies, where workers undertake the same tasks without knowing how their earnings will be determined. Our research adds to the fairness literature by investigating how people perceive the fairness of substantial wealth transfers from wealthy parents to their children.

Our study also complements recent studies by Freyer and Günther (2022) and Cohen et al. (2022), which examine fairness preferences when income is determined by friends or strangers initially designated to work solely for the workers. They find no significant difference between self-earned and designated wealth. The insights from Freyer and Günther (2022) and Cohen et al. (2022) are valuable for understanding scenarios where third parties, such as trust fund managers, public officials, or legal guardians, act merely as wealth designators. Our study introduces several key differences that capture the unique aspects of intergenerational wealth transfers. First, our setup involves actual parents making decisions, providing a culturally relevant perspective on familial wealth transfers. Second, it allows parents to directly benefit from their earnings rather than working solely for their children's benefit. Third, wealthy parents decide whether to pass on their advantages to the next generation by transferring a portion of their wealth.[5]

A notable contemporary working paper by Bhattacharya and Mollerstrom (2024) also explores fairness preferences over intergenerational wealth transfers. Their study recruits only parents who transfer earned money to various beneficiaries—themselves, their child, or a random child—with the transfer to the child conducted via a gift card sent to the child's email. Spectators then make redistributive decisions among these different beneficiaries. They find a mild aversion to unequal intergenerational transfer: the inequality acceptance of children's inherited merit

[5] Pogliano (2024) explores how individuals' beliefs about genetics' role in generating performance inequality affect redistribution preferences. Lekfuangfu et al. (2023) investigates how fairness preferences change when some workers have better opportunities due to decisions made by a stranger.

is lower than parents' self-earned merit but significantly higher than parents' self-luck, with no substantial difference between children's inherited luck and parents' self-luck. Our experiments differ in three key areas, emphasizing our unique contributions to the literature.

First, in the intergenerational treatments by Bhattacharya and Mollerstrom (2024), parents earned the same and worked solely for their children. This setup mirrors scenarios where parents across the same social class exert extra effort to support their children. In contrast, our study allows advantaged parents to retain benefits from their earnings after making transfers. This approach minors real-world situations where inequality in wealth transfers often originates from economically advantaged parents choosing to pass on their advantages through transfers (Corak, 2013).[6] We find a pronounced inequality aversion over transferred wealth, in contrast to the mild aversion observed by their study. Second, methodologically, Bhattacharya and Mollerstrom (2024) solely recruit parents, hence requiring spectators to redistribute among various beneficiaries, including parents and children. In addition, their treatments of parents' luck and children's intergenerational transfers do not have a work component. In contrast, our study recruited both parents and children. Following Almås et al. (2020), we ensure all child workers, irrespective of their income source, complete the same assignments without prior knowledge of the payoff rules. Then, the spectator redistributes earnings for children workers. This design controls for various spectator beliefs beyond differing income sources, such as beliefs about the effort across treatments and differing payoff needs between parents and children. Third, Bhattacharya and Mollerstrom (2024) focus solely on an American sample, while our study expands to include a Chinese cohort, revealing noticeable differences between the two countries. This extension enriches recent research exploring variations in fairness perceptions between the U.S. and Europe, typically centering on Scandinavian countries (Almås et al., 2020).[7]

Finally, this paper contributes to research examining the economic implications

[6] This also suggests that the primary motivation for wealth accumulation often focuses on personal advancement and security rather than solely transferring wealth (e.g., Horioka and Watanabe, 1997; Ameriks et al., 2020).

[7] Cappelen et al. (2022b) compared fairness preferences between individuals in Shanghai, China, and Norway.

of intergenerational wealth transfers. The foundational works of Kotlikoff and Summers (1981) and Modigliani (1988) initiated the exploration of this topic. The research conducted by Piketty (2011) and Piketty (2014) revitalized interest in it. For instance, studies by Black et al. (2020) and Fagereng et al. (2021) have investigated the role of these transfers in shaping the wealth and other economic outcomes of the next generation. Furthermore, researchers such as Boserup et al. (2016), Adermon et al. (2018), Elinder et al. (2018), Black et al. (2022), and Nekoei and Seim (2023) have focused on the implications of unequal intergenerational transfers on aggregate wealth inequality. Additionally, Bastani and Waldenström (2021) examined how the provision of information regarding the effects of unequal intergenerational transfers influences public attitudes toward inheritance taxation. Our study adds to this dialogue by providing a precise measurement of public fairness perceptions concerning intergenerational wealth transfers.

2 Experimental Design

We adapt the framework established by Almås et al. (2020), incorporating necessary modifications to align with our research objectives. The experiment involved three distinct groups: workers, their parents, and spectators. All workers were tasked with completing the same assignment, but their initial earnings were influenced by luck, performance, or parental transfers. Similarly, parents completed assignments with their initial earnings determined by luck or performance. An impartial third party, the spectators, was responsible for deciding how to redistribute the earnings among pairs of workers. This experiment focuses on the allocation decisions made by these spectators. The structure and implementation of the experiment are detailed below, with experimental protocols for all participant types provided in Appendix D-F.

2.1 Workers and Parents

The workers in the study were students from Huazhong University of Science and Technology. Each participant was promised a participation fee of 30 CNY for a 15-minute experiment, with the possibility of earning additional money based on their and others' actions during the study. Parents were also offered 30 CNY for participating in a 15-minute experiment and could earn additional money based on their actions. Importantly, the payment was conditional on the participation of both students and their parents.

Before the experiment, students were instructed to coordinate with their parents to select one of the available 15-minute slots over the weekend. This arrangement allowed students to participate in the university lab and their parents to participate remotely. They were also advised to ensure their parents prepared a photograph of an official document, i.e., a Hukou booklet, for upload during the experiment to verify against the student's enrollment records.[8] Upon arrival at the lab, students provided their parent's phone numbers, and we sent survey links to the parents. It is important to note that during the experiment, students were prohibited from using personal electronic devices, so they could not communicate with their parents during the experiment.

A total of 280 workers, along with their parents, participated in our main experiment, completing four different assignments, including math and logical reasoning questions. Upon completing all assignments, workers were informed about their compensation. The earnings for each assignment were determined according to pre-established payment rules. However, to ensure workers exerted the same effort across different treatments, these rules were not disclosed to the workers before or after the assignments. Additionally, each worker was paired with another for each assignment, creating 560 unique worker pairs. We informed workers that a third party would be aware of the assignment details and the initial distribution of earnings, and this third party would have the opportunity to redistribute earnings between the two workers in each pair, thus determining their actual pay for the assignment.

Similarly, the parents completed four assignments. Upon completion, parents were informed that pre-established rules determined their earnings for each assignment. To ensure consistent effort across treatments, these rules were not disclosed to the parents either before or after the assignments.

[8] A Hukou booklet is issued per family and includes all members' births, deaths, marriages, divorces, and residential moves. Only the pages displaying all family members' names, birth dates, and family relationships are required. See Appendix F. For privacy reasons, we deleted the photograph after verification.

2.2 Treatments

We implemented six between-subjects treatments, varying the sources of workers' initial earnings.

Self-earned In the Luck treatment (L), initial earnings were determined by a lottery. 50% of workers randomly received 6 points each, while the rest received none. In the Merit treatment (M), earnings were performance-based. Workers scoring above the median among their peers received 6 points, while those below did not receive any points, maintaining a 50% chance of obtaining earnings.[9] Points were converted to actual currency at a rate of 1 point to 1 CNY.

Intergenerational transfer decided by parents In the Merit-Parent (MP) and Luck-Parent (LP) treatments, workers' initial earnings were determined by earnings transferred from their parents. Parents completed four assignments, after which they were informed their compensation would adhere to predetermined payment rules. The distinction between MP and LP rested on the point-earning rule. In the MP treatment, parents earned 15 points if their performance exceeded the median level of their peers. In the LP treatment, 50% of parents randomly received 6 points each, while the rest received none. Parents had the option to transfer 6 points to their children or retain the full amount. They were informed that this transfer would determine their child's final payment, although other factors might also play a role. They also knew that transferred points were converted into funds on the student's college card, usable only within the college and non-convertible to cash. Parents were assured of the anonymity of their decisions.[10]

Intergenerational Transfer without parents' decisions We introduced two additional treatments, MPN and LPN, where N stands for "no choice." These treatments paralleled MP and LP, except that for parents earning 15 points, we automatically transferred 6 points to their children. We explained that the transfer would determine their child's final payment, although other factors might also play a role. The six treatments are structured as follows:

[9] Performance was first ranked based on the number of correct answers and then further ranked based on speed.

[10] 75% of parents chose to transfer their earnings in the experiment.

1) *L*: Worker's wealth inequality is attributed to luck.

2) *M*: Worker's wealth inequality is based on assignment performance.

3) *LP*: Worker's wealth inequality stems from parental transfer choices, where parents' earnings are determined by luck.

4) *MP*: Worker's wealth inequality originates from parental transfer choices, where parents' earnings are based on performance.

5) *LPN*: Worker's wealth inequality stems from automatic parental transfers, with parents' earnings determined by luck.

6) *MPN*: Worker's wealth inequality originates from automatic parental transfers, with parents' earnings based on performance.

2.3 Spectator

Spectators were randomly assigned to one of six treatments, each paired with a unique pair of workers. Their task was to decide whether and how much to redistribute the workers' initial earnings. We emphasized that, unlike typical survey responses, their choices could significantly impact real-life outcomes, given a 10% chance of actual implementation.[11,12] At the end of the experiment, spectators completed a non-incentivized survey addressing their views on inheritance tax policies, along with several background questions.

To manage potential variation in worker earnings, we employed a contingent response method, where spectators made redistribution decisions across three possible scenarios: one worker earning 6 points and the other 0 points, both earning 6 points, or neither earning any points. Spectators were not informed of the actual scenario to ensure they considered each decision carefully.[13] To maintain clarity for international spectators, the term "points" was used instead of the local currency

[11] Charness et al. (2016) discusses the merits and drawbacks of implementing decisions for only a subset of participants versus full implementation, finding little significant difference between these approaches. Additionally, Clot et al. (2018) find the decisions in the dictator game are consistent across a 10% implementation probability and 100% implementation probability.

[12] Six pairs were not assigned an actual spectator; instead, we simulated spectator decisions by distributing earnings equally. This was necessary because, with 5,537 spectators and a 10% implementation rate, we anticipated needing 553 pairs, yet we had 540 pairs available.

[13] Brandts and Charness (2011) report that the contingent response and strategy methods typically yield similar outcomes to direct-response methods. Notably, no studies they reviewed failed to replicate treatment effects found with contingent responses using direct methods.

name. Our analysis focuses on scenarios with unequal earnings to explore spectators' fairness views. Hence, decisions regarding unequal distribution scenarios are solicited first.

Spectators were thoroughly briefed about the conditions and information previously provided to workers and their parents. This comprehensive disclosure is crucial for interpreting our results. First, spectators knew workers did not know the payment rules before or after completing their tasks. This procedure ensured that spectators understood that the workers' efforts were consistent across treatments. Second, it was clear to spectators that workers would remain uninformed about their earnings throughout the experiment. This approach aimed to minimize the influence of worker expectations on spectators' decisions.[14] Third, spectators were not aware of the workers' nationalities, maintaining the focus on economic behaviors rather than cultural or national identity.

To address potential concerns that merely knowing how a worker's parent's earnings were determined—without actual intergenerational transfers—might affect a spectator's fairness judgments, we randomly disclosed to spectators in both the Merit (M) and Luck (L) treatments whether the parent's earnings were determined by merit or luck. Our analysis shows that this information did not influence the decisions (see Appendix Table A5 and Table A6). Therefore, in this paper, we refer to these treatments simply as M and L without specifying how the parents' earnings were determined.

The fairness judgments of spectators, who, as third parties, have no financial stake in the outcomes, serve as a robust measure of fairness and inequality perceptions (e.g., Almås et al., 2020; Andreoni et al., 2020). This method offers a significant benefit, contrasting with the standard dictator game and dictator games under the veil of ignorance. Specifically, the decisions of spectators involve no personal financial trade-offs, ensuring that observed differences in distribution choices are not due to individual material self-interests.

[14] However, as tested in a robustness study by Almås et al. (2020), spectators' behavior is not affected even when they know workers have been informed about their initial earnings.

2.4 Rationale Behind Design Features

First, it is important to highlight the differences in our method compared to the approach used by Almås et al. (2020). In their study, the allocation of earnings within paired work settings was structured as a zero-sum game, where the success of one worker was directly tied to the loss of another, consistently awarding one worker 6 USD and the other none. Conversely, our method allows both workers within the pair to earn an income, assigning earnings based on each worker's luck, merit, or earnings transferred from their parents, independent of the other worker. This design aims to naturally stimulate intergenerational transfers, where children's receipts depend solely on their parents' decisions rather than a competitive comparison with another worker's parent. As noted by Schaube and Strang (2023), unlike in the settings of Almås et al. (2020) where only one worker receives earnings, allowing both workers the potential to earn leads to greater acceptance of inequality. For instance, permitting both individuals to succeed simultaneously in luck treatments reduces the redistribution towards low-income earners by up to 20% in a sample of German students.[15]

Second, parents' initial earnings exceed 6 points, allowing them to retain a significant portion of their wealth even after making transfers. This design contrasts sharply with the "designator" approach, where parents work solely for their children's benefit. We incorporated this feature to highlight that inequality in wealth transfers often originates from economically advantaged parents who, after benefiting from their own earnings, choose to pass on their advantages through transfers. Such a phenomenon is prevalent in Europe and North America, particularly in the U.S. (Corak, 2013). Furthermore, this design reflects the idea that motivations for working and saving are centered on personal benefits, such as precautionary measures, retirement planning, and the social benefits of wealth. In contrast, the significance of motives for saving for children remains contentious and is often found to be relatively mild if not insignificant (e.g., Horioka and Watanabe, 1997; Ameriks

[15] Schaube and Strang (2023) observed that as long as the payoff structure within the pair does not entirely depend on each other, it does not matter whether the chances of winning are still partly influenced by the other worker or are entirely independent of one another.

et al., 2020, and others).[16]

Table 1. Background Variables for the Spectator Sample

	U.S. Sample	U.S. Pop.
Demographics		
Age	49	48
% White	66	64
% Female	51	51
% Has at Least a 4-Year College Degree	46	33
% Northeast	19	18
% Midwest	19	21
% South	41	38
% West	21	23
Financial Characteristics		
% Household Income $\leq$ 50K USD	39	39
% Household Income 50K-100K USD	32	30
% Household Income 100K+ USD	29	31
Political affiliation		
% Democrat	38	31
% Independent	29	41
% Republican	28	28
% Prefer not to say or don't know	6	
Number of participants	2,824	

	China Sample	China Pop.
Demographics		
Age	39	42
% Han Ethnic	95	91
% Female	53	51
% Has at Least Some College Degree	67	17
% Tire 1 City	36	6
% Tire 2 City and Below	64	94
Financial Characteristics		
% Household Income $\leq$ 120K CNY	66	80
% Household Income 120K+ CNY	34	20
Number of participants	2,713	

Note: This table presents a comparison of the survey participants' characteristics against the average characteristics of both the U.S. adult population and the adult population of China. For the U.S., demographic and financial characteristics are compared to data from the 2021 American Community Survey, while political affiliations are compared to 2023 Gallup polling results. For the Chinese population, the comparison is based on statistics from the 2020 Seventh National Population Census.

2.5 Implementation of Spectator Experiment

We recruited spectators from the U.S. and China via Dynata, a leading online sampling company with a panel of over 62 million members who receive cash and vouchers as incentives for survey participation. As noted by Haaland et al. (2023), Dynata is commonly used by researchers for conducting survey-based studies. Eligibility criteria required respondents to reside in the United States or China and be at least 18 years old. For the U.S. sample, Dynata ensured a representative sample aligned with national averages in terms of gender, age, race, and census region. In China, the sample was targeted to reflect specific demographics, including age, ethnicity, gender, city tier level, and household income. Participants completed the survey on Qualtrics, where treatment assignment and randomization were conducted at the individual level using the platform's built-in features.

To enhance the quality of survey responses, we implemented multiple strate-

[16] Furthermore, this design mirrors the real-world situation where older generations typically possess significantly higher net wealth than younger ones, particularly due to the appreciating value of their assets. For instance, according to the 2023 Survey of Consumer Finances by the Federal Reserve, the median U.S. household net worth is $120,000. However, for Americans over 50, it is more than triple that amount.

gies. Initially, an attention check was conducted to filter out inattentive participants and potential bots. Participants were also required to pass a quiz on the instructions before proceeding. We also excluded responses from participants who completed the survey in less than 2 minutes or more than 60 minutes—representing the top 1% and bottom 1% of completion times, with the median completion time being approximately 10 minutes. Moreover, we screened for straight-lining bias, where respondents might consistently choose the first or last response option in demographic questions. Our analysis showed that this bias was not detected across the dataset.

Table 1 displays the demographic characteristics of our survey respondents and compares them with the general adult populations in their respective countries. Appendix A Table A1 and Table A2 report the demographic statistics for each treatment within the country. For the U.S. sample, the national average statistics are sourced from the 2021 American Community Survey and the 2023 Gallup polling results. Similarly, the population statistics for the Chinese sample draw on data from the 2020 Seventh National Population Census. While age, gender, race, census region, household income, and political affiliation in the U.S. sample generally mirror national statistics, there is an overrepresentation of college-educated respondents. Our Chinese sample seems less representative: it includes a higher proportion of college graduates, residents of first-tier cities (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen), and individuals with higher household incomes. This disparity in the Chinese sample reflects limited internet access among less advantaged groups.

We present the weighted statistics in Section 3 to ensure representativeness and adjust for these demographic discrepancies. The weighting process adjusts sample weights to ensure alignment with demographic and financial characteristics as reported by the 2021 American Community Survey for the U.S. and the 2020 Seventh National Population Census for China.[17]

[17] In our analysis, we employ the numerical iterative method known as raking to compute the weights. The raking process iteratively adjusts weights assigned to each respondent until the sample distribution matches the target population characteristics across all specified variables. Weights in the China sample range from 0.9 to 3.4 and from 0.4 to 2.4 in the U.S. sample, which is considered reasonable within this statistical context.

3 Results

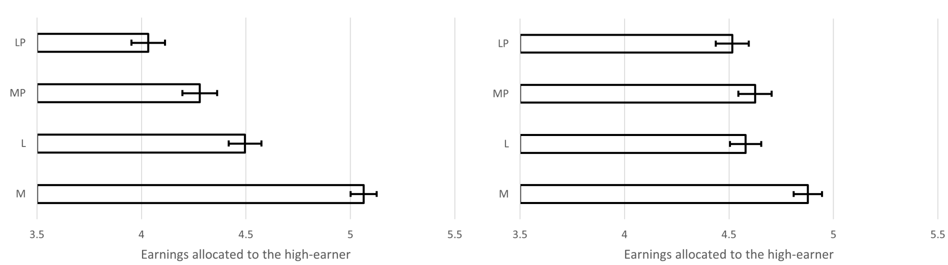
In this section, we outline our study's main findings, which focus on spectator decisions in scenarios of unequal earnings distribution: high earners receive 6 points while low earners receive none. See Appendix C for an analysis of spectator decisions when both workers have identical earnings. Section 3.1 compares outcomes between earnings self-earned (M and L treatments) and those determined by intergenerational transfers (MP and LP treatments). Section 3.2 examines the effects of intergenerational transfers without parental choice (MPN and LPN treatments). Section 3.3 provides additional analyses for further robustness.

3.1 Self-Earned vs. Parent-Determined Transfers

Following the analytical framework of Almås et al. (2020), we first provide a descriptive overview of spectator choices, then conduct a detailed statistical analysis of treatment effects, and finally explore heterogeneity treatment effects among various demographic groups.

Figure 1: Average Level of Earnings Allocated to the High-Earner in Each of Four Treatments

(a) U.S. (b) China



Note: This figure illustrates average level of earnings allocated to the high-earner by Americans and Chinese in each of four treatments. The robust standard errors are indicated by the bars.

Descriptive Statistics Figure 1 presents the average percentage of earnings allocated to high earners across treatments by country. At first glance, the treatment variance among Americans is larger than that observed among the Chinese. Specifically, Americans allocated 84%, 75%, 71%, and 67% of total earnings to high earners in the M, L, MP, and LP treatments, respectively. Conversely, Chinese spectators allocated 81%, 76%, 77%, and 75% in the corresponding treatments. Appendix Figure A1 shows the histograms of spectator choices across treatments.

As mentioned, our L and M treatments are similar to those in Almås et al. (2020). In their study, American spectators allocated 77% and 67% to high-income earners in their M and L treatments, respectively. In comparison, we observe 84% and 75% allocations in our study. This indicates that our sample is more accepting of inequality, particularly in the L treatment. However, the difference between L and M treatments persists. As noted in the experimental design section, this difference may be attributed to our allowance for both workers to succeed. Consequently, our findings align with Schaube and Strang (2023), which shows that enabling both workers to succeed reduces transfers to low-income earners by up to 20%.

When comparing spectator choices between the U.S. and China, in the L treatment—where earnings are based purely on luck—there is no significant difference in the allocation to high earners between American and Chinese spectators ($p = 0.44$). However, in the M treatment, where earnings depend on individual performance, Americans allocate significantly more to high earners than the Chinese ($p = 0.04$). Moreover, in the MP and LP treatments, where earnings stem from parental transfers, Americans allocate significantly less to high earners compared to the Chinese ($p < 0.01$). Appendix A Table A7 provides a detailed statistical analysis of these cross-country differences.

Treatment Effets We now examine how implemented inequality varies by treatment. The primary variable of interest is the inequality implemented by spectator i, defined as:

$$e_i = \frac{|\text{income of worker } A_i - \text{income of worker } B_i|}{\text{total income}} \in [0, 1] \tag{1}$$

Here, worker A_i represents the individual with higher pre-redistribution earnings. This inequality measure corresponds to the Gini coefficient for two-person scenarios. A value of 1 indicates no redistribution by the spectator, while a value of 0 indicates complete earning equalization between the two workers.

While Almås et al. (2020) focused primarily on implemented inequality, our analysis incorporates two additional variables to enhance the robustness of our findings: (1) the proportion of earnings allocated to the higher earner, and (2) a dummy variable indicating whether a spectator allocates more earnings to higher earners.

The main empirical approach employs a robust OLS regression:

$$y_i = \alpha + \alpha_M M_i + \alpha_{MP} MP_i + \alpha_{LP} LP_i + \gamma \mathbf{X}_i + \varepsilon_i \tag{2}$$

In this model, y_i represents one of the three main outcome variables of interest as specified, with M_i, MP_i, and LP_i serving as indicators for whether spectator i is in the Merit, Merit-Parent, or Luck-Parent treatment, respectively. The Luck treatment serves as the reference category, and estimates are interpreted relative to this baseline.

Analyses are conducted separately for samples from the U.S. and China. The vector $\mathbf{X}_i$ includes control variables such as age, gender, race, census region, education level, household income, and political affiliation for Americans, and age, gender, ethnicity, education level, household income, and city tier level for Chinese. While our primary analysis incorporates these controls, results from regressions without control variables are also presented and discussed. Additionally, we report regression results that have been re-weighted to align with the nationally representative sample.

Table 2 presents the regression results for the U.S. sample (Panel A) and China sample (Panel B).[18] Column titles correspond to the outcome variables examined.

We begin by examining the estimated causal effect of replacing luck with merit as the source of inequality, facilitating comparison with existing literature. In the U.S., the effect (coefficient α_M) is positive and significant across three outcome variables: it increases the average earnings allocated to high earners, the probability of allocating more earnings to high earners, and the implementation of inequality. This treatment effect remains robust across all regression models, irrespective of controlling for background variables or reweighting the samples ($p < 0.01$). Conversely, in China, the shift from luck to merit as the source of

[18] To conserve space, coefficients for control variables are omitted. Full estimates for the U.S. and China samples are provided in the corresponding Appendix Table A4 and A3.

Table 2. Regression Results on Spectator Decisions

Panel A: U.S.	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.568***	0.575***	0.487***	0.184***	0.180***	0.162***	0.130***	0.131***	0.111***
	(0.100)	(0.101)	(0.110)	(0.028)	(0.028)	(0.030)	(0.026)	(0.026)	(0.028)
MP	-0.217*	-0.191*	-0.241**	-0.055*	-0.048	-0.055	-0.036	-0.026	-0.057*
	(0.114)	(0.114)	(0.120)	(0.032)	(0.032)	(0.034)	(0.029)	(0.029)	(0.031)
LP	-0.463***	-0.447***	-0.573***	-0.144***	-0.141***	-0.164***	-0.116***	-0.107***	-0.130***
	(0.112)	(0.113)	(0.123)	(0.032)	(0.032)	(0.034)	(0.029)	(0.030)	(0.031)
R-squared	0.052	0.060	0.064	0.063	0.079	0.081	0.042	0.062	0.065
N	1,852	1,852	1,852	1,852	1,852	1,852	1,852	1,852	1,852
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Wald-test									
LP-MP	-0.247**	-0.257**	-0.332***	-0.089***	-0.092***	-0.110***	-0.080***	-0.081***	-0.074**
	(0.115)	(0.116)	(0.124)	(0.033)	(0.033)	(0.035)	(0.030)	(0.030)	(0.032)
M-MP	0.785***	0.766***	0.728***	0.239***	0.229***	0.216***	0.166***	0.157***	0.167***
	(0.104)	(0.104)	(0.112)	(0.029)	(0.029)	(0.031)	(0.027)	(0.027)	(0.029)
Panel B: China									
	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.297***	0.271***	0.271*	0.113***	0.109***	0.133***	0.084***	0.077***	0.083**
	(0.101)	(0.100)	(0.147)	(0.027)	(0.027)	(0.039)	(0.025)	(0.024)	(0.034)
MP	0.045	0.049	0.263*	-0.015	-0.014	0.057	0.022	0.026	0.073*
	(0.109)	(0.109)	(0.156)	(0.030)	(0.031)	(0.043)	(0.027)	(0.027)	(0.039)
LP	-0.065	-0.056	0.171	-0.023	-0.022	0.064	0.004	0.006	0.064*
	(0.109)	(0.108)	(0.150)	(0.030)	(0.030)	(0.041)	(0.027)	(0.026)	(0.036)
R-squared	0.007	0.029	0.032	0.016	0.030	0.030	0.008	0.029	0.040
N	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Wald-test									
LP-MP	-0.109	-0.106	-0.092	-0.008	-0.008	0.007	-0.018	-0.019	-0.009
	(0.112)	(0.112)	(0.157)	(0.031)	(0.031)	(0.042)	(0.027)	(0.027)	(0.038)
M-MP	0.252**	0.222**	0.008	0.128***	0.123***	0.076*	0.062**	0.051**	0.010
	(0.105)	(0.105)	(0.155)	(0.028)	(0.028)	(0.040)	(0.025)	(0.025)	(0.037)

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |$income of worker A $-$ income of worker B$|/$total income. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", and "LP" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, and luck-parent treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

inequality yields a positive but smaller and less consistently significant effect when reweighting the sample and controlling for background variables. The reduced causal impact indicates a less pronounced sensitivity to the source of inequality (luck versus merit) among Chinese populations.

Result 1*: Merit, rather than luck, as the source of inequality leads to a significant increase in inequality acceptance in both the U.S. and China, with the effect being more pronounced in the U.S. sample.*

We now turn to the main findings related to intergenerational transfer to address our research questions. In the U.S., inequality acceptance is significantly higher when parents' earnings are derived from merit rather than luck, as reflected in all three outcome variables (coefficient $\alpha_{MP} - \alpha_{LP}$). However, in the Chinese sample, the difference between coefficients α_{MP} and α_{LP} is not significant, regardless of the regression model or outcome variables used.

Result 2*: Americans show a preference for intergenerational meritocracy, as their acceptance of transferred inequality is higher when a parent's earnings are merit-based rather than luck-based. However, this preference is not observed among the Chinese.*

Finally, analyses of American and Chinese samples reveal distinct fairness preferences toward inequality in intergenerational contexts compared to self-earned contexts. When the source of inequality shifts from self-luck or self-merit to parent-transferred wealth derived from parental luck or merit, Americans exhibit a significant decrease in their acceptance of inequality. Specifically, the regression coefficients $\alpha_{MP} - \alpha_M$ and α_{LP} are consistently negative and significant across all models, indicating a strong aversion to intergenerational inequality. Notably, acceptance levels in the MP treatment are even lower than in the L treatment. However, these differences are not consistent across all models. In contrast, for Chinese participants, the coefficient α_{LP} does not demonstrate. While the difference $\alpha_{MP} - \alpha_M$ initially appears as significantly negative, it loses significance after sample reweighting. These findings underscore substantial cultural differences in perceptions of intergenerational inequality.

Result 3*: Americans exhibit a stronger aversion to inequality stemming from intergenerational wealth transfers compared to self-earned wealth. While the Chinese also show this aversion, it is much milder.*

Heterogeneity Analysis We now turn to an analysis of the heterogeneity in treatment effects across various demographic groups. Appendix B provides a detailed analysis along with the related tables. Overall, the treatment effects are remarkably consistent across subgroups and countries.

Specifically, in the U.S., the aversion to unequal intergenerational wealth transfers is robust across most groups, except for households earning more than \$100K annually. These households do not exhibit a lower acceptance of inequality when it originates from transfers from lucky parents compared to self-derived luck. Furthermore, the intergenerational meritocracy fairness view is largely upheld, with exceptions noted among high-income individuals and those with college degrees.

Similarly, in China, attitudes towards unequal intergenerational transfers across various subgroups are generally in line with the aggregate findings. Many subgroups show no aversion to unequal intergenerational wealth transfers, while others display only a mild aversion. Taken together, this heterogeneity analysis corroborates our main findings (Results 1-3) in both the U.S. and China.

3.2 Transfers Without Parental Choice

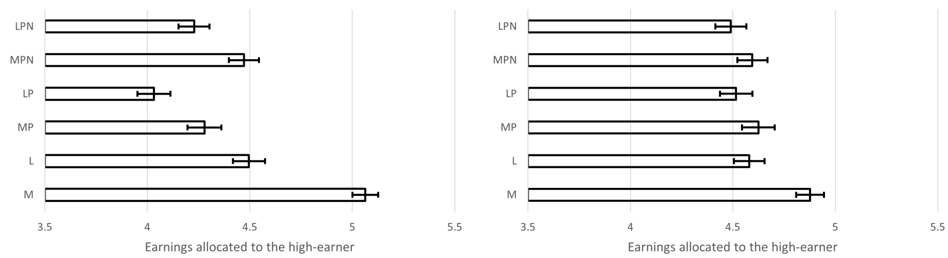
In the MP and LP treatments, where parents can decide whether to transfer earnings to their children, the sources of inequality among children are twofold. First, economically advantaged parents—either due to superior performance or luck—have earnings to transfer, while disadvantaged parents do not. Second, among parents who have the means to transfer, some choose to do so, while others opt not to. In contrast, the MPN and LPN treatments remove the element of parental choice. Therefore, people's attitudes towards unequal intergenerational wealth transfers are influenced solely by the power dynamics of whether parents possess wealth to transfer.

Figure 2 illustrates the average percentage of earnings allocated to high earners across all six treatments by country. Appendix Figure A2 displays histograms of spectator choices across these treatments, segmented by country. The data suggest a negligible effect of parental active choice on perceptions of fairness towards intergenerational wealth transfers, as transfers in the MP and LP treatments are similar to those in the MPN and LPN treatments. For instance, in the U.S. sample, the average transfers to high earners in the MP, LP, MPN, and LPN treatments are 71%, 67%, 74%, and 69%, respectively. Likewise, in the Chinese sample, these figures

Figure 2: Average Level of Earnings Allocated to the High-Earner in Each of Six Treatments

(a) U.S.

(b) China



Note: This figure illustrates average level of earnings allocated to the high-earner by Americans and Chinese in each of six treatments. The robust standard errors are indicated by the bars.

are 77%, 75%, 77%, and 75%.

Complementing this descriptive evidence, Table 3 presents regression results for Equation 2, covering all six treatments. The findings from the MPN and LPN treatments support those from the MP and LP treatments; notably, Americans exhibit a greater acceptance of inequality in the MPN than in the LPN, a pattern not observed among Chinese. Moreover, Americans display a strong aversion to intergenerational inequality in the MPN and LPN treatments compared to self-earned inequality in the L and M treatments. Additionally, we replicate the heterogeneity analysis for the MPN and LPN treatments. The corresponding results are detailed in Appendix Table A8. The results are consistent with those from the MP and LP treatments.

Result 4: *People's attitudes toward inequality caused by intergenerational wealth transfers are primarily shaped by whether parents possess wealth to transfer rather than their decision to transfer it.*

Table 3. Regression Results on Spectator Decisions for All Treatments

Panel A: U.S.	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.568***	0.565***	0.483***	0.184***	0.179***	0.162***	0.130***	0.131***	0.112***
	(0.100)	(0.101)	(0.110)	(0.028)	(0.028)	(0.030)	(0.026)	(0.026)	(0.028)
MP	-0.217*	-0.199*	-0.249**	-0.055*	-0.050	-0.056	-0.036	-0.025	-0.056*
	(0.114)	(0.114)	(0.120)	(0.032)	(0.032)	(0.034)	(0.029)	(0.029)	(0.031)
LP	-0.463***	-0.451***	-0.574***	-0.144***	-0.141***	-0.164***	-0.116***	-0.106***	-0.129***
	(0.112)	(0.113)	(0.123)	(0.032)	(0.032)	(0.034)	(0.029)	(0.029)	(0.031)
MPN	-0.024	-0.013	-0.079	-0.014	-0.016	-0.031	-0.029	-0.019	-0.039
	(0.107)	(0.109)	(0.118)	(0.031)	(0.031)	(0.033)	(0.029)	(0.029)	(0.031)
LPN	-0.267**	-0.255**	-0.366***	-0.080**	-0.081**	-0.099***	-0.088***	-0.080***	-0.097***
	(0.109)	(0.109)	(0.120)	(0.032)	(0.032)	(0.034)	(0.029)	(0.029)	(0.031)
R-squared	0.037	0.045	0.047	0.044	0.062	0.062	0.032	0.053	0.054
N	2,824	2,824	2,824	2,824	2,824	2,824	2,824	2,824	2,824
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Wald-test									
LPN-MPN	-0.243**	-0.242**	-0.288**	-0.066**	-0.065**	-0.068**	-0.059**	-0.061**	-0.059*
	(0.105)	(0.105)	(0.118)	(0.031)	(0.031)	(0.034)	(0.029)	(0.028)	(0.031)
M-MPN	0.592***	0.578***	0.561***	0.198***	0.195***	0.193***	0.159***	0.150***	0.151***
	(0.096)	(0.098)	(0.109)	(0.028)	(0.028)	(0.030)	(0.026)	(0.026)	(0.029)

Panel B: China	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.297***	0.278***	0.276*	0.113***	0.110***	0.134***	0.084***	0.078***	0.085**
	(0.101)	(0.100)	(0.148)	(0.027)	(0.027)	(0.039)	(0.025)	(0.024)	(0.034)
MP	0.045	0.048	0.259*	-0.015	-0.015	0.056	0.022	0.025	0.072*
	(0.109)	(0.109)	(0.156)	(0.030)	(0.031)	(0.043)	(0.027)	(0.027)	(0.039)
LP	-0.065	-0.063	0.164	-0.023	-0.023	0.062	0.004	0.005	0.063*
	(0.109)	(0.108)	(0.150)	(0.030)	(0.030)	(0.041)	(0.027)	(0.026)	(0.036)
MPN	0.015	-0.023	0.203	-0.013	-0.024	0.021	-0.017	-0.016	0.032
	(0.105)	(0.108)	(0.167)	(0.030)	(0.031)	(0.049)	(0.027)	(0.028)	(0.045)
LPN	-0.090	-0.134	0.005	-0.051	-0.063**	-0.044	-0.042	-0.039	0.014
	(0.106)	(0.109)	(0.184)	(0.031)	(0.032)	(0.051)	(0.027)	(0.028)	(0.045)
R-squared	0.007	0.019	0.026	0.014	0.022	0.027	0.010	0.021	0.030
N	2,713	2,713	2,713	2,713	2,713	2,713	2,713	2,713	2,713
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Wald-test									
LPN-MPN	-0.105	-0.111	-0.198	-0.038	-0.039	-0.065	-0.025	-0.023	-0.018
	(0.105)	(0.105)	(0.192)	(0.031)	(0.031)	(0.054)	(0.028)	(0.028)	(0.050)
M-MPN	0.282***	0.301***	0.073	0.125***	0.134***	0.113**	0.101***	0.094***	0.053
	(0.100)	(0.102)	(0.165)	(0.028)	(0.028)	(0.046)	(0.025)	(0.026)	(0.043)

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |\text{income of worker A} - \text{income of worker B}|/\text{total income}$. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", "LP", "MPN", and "LPN" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, luck-parent treatment, merit-parent-no-choice treatment, and luck-parent-no-choice treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Underlying psychological mechanism What psychological mechanisms drive the aversion to inequality resulting from intergenerational wealth transfers compared to self-earned wealth? We propose two main reasons. First, spectators might aggregate the wealth between children and parents in intergenerational transfer treatments. This idea, when applied to real life, suggests that individuals might view the tax system for self-earned earnings as inherently unfair and seek to rectify this through more pronounced redistribution in cases of transferred wealth. However, insights from recent literature and our data analysis suggest this explanation is unlikely. For instance, a recent study by Exley and Kessler (2024) presented an experiment environment where an individual's payoff includes multiple components. In such settings, the tendency to aggregate payoff components should be more pronounced than in our scenario, which focuses on individual components. Despite this, their experimental results indicate that spectators typically exhibit narrow equity concerns, applying fairness principles specifically to distinct components of payoffs rather than to the overall financial outcomes.

Furthermore, if the aggregation conjecture were valid, we would expect a higher likelihood of spectators redistributing more than half of the wealth to low-income children in intergenerational contexts (MP, LP, MPN, LPN) compared to self-earned contexts (M and L). Contrary to this hypothesis, only a small fraction of spectators (approximately 6%) across both countries choose to allocate more than half of the total earnings to the child without initial earnings. Appendix Table A10 displays regression results, which show no significant differences in allocation behavior between self-earned and intergenerational contexts. Additionally, in Appendix Table A9, we replicate our regression by excluding spectators who allocate more to the worker without initial earnings. The results are qualitatively similar to the previously estimated treatment differences in Table 3.

The second potential explanation involves the negative perception of intergenerational mobility. This perception intensifies when wealthy parents, already advantaged by their wealth, continue to influence economic outcomes for future generations through these transfers. Alesina et al. (2018) found that perceptions of low intergenerational mobility increase support for redistribution policies. In scenarios involving intergenerational transfers, the "wealthy" parents perpetuate advantages, reinforcing the cycle of intergenerational mobility.

Finally, why do Chinese individuals only have mild aversions to inequality from intergenerational wealth transfers? In the United States, cultural values strongly emphasize individualism. This ethos supports the belief that success should stem from personal achievements rather than external factors such as family wealth. Conversely, Chinese culture, deeply influenced by Confucianism, emphasizes family harmony and obligations (Qi, 2015). Consequently, wealth transfers within families are often viewed more favorably as a continuation of support and duty across generations. This cultural perspective likely leads to a more accepting view of intergenerational wealth transfers, regarded as fulfilling familial roles and responsibilities.

3.3 Further Analysis

One might be concerned that participants misunderstood the experiment and randomly made redistribution choices, as their decisions did not affect their payoffs. We conducted a robustness check to address these concerns. Since we applied the strategic method, we also recorded spectator allocation choices when both workers had 6 points in their initial earnings. In this scenario, irrespective of their preferences, spectators should allocate 6 points to both workers. A failure to do so could indicate randomization in their choices. In Appendix C, we excluded these potentially low-quality responses and repeated the analysis presented in Table 2. The findings, detailed in Table C2, align with our main results, reinforcing the robustness of our conclusions.

To study whether the distributive behavior in the experiment is associated with the attitudes towards redistributive policies, we examined spectators' views on inheritance tax at the end of the experiment. The analysis, detailed in Appendix Table A11, involves a regression of attitudes towards inheritance tax on the implemented inequality, controlling for all background variables. This analysis was conducted in two different contexts: the self-earned context (L and M treatments) and the intergenerational transfer context (MP and LP treatments).

In the U.S., Republicans, older individuals, and white participants are more likely to oppose inheritance taxes. Notably, the implemented inequality in the intergenerational context (MP and LP treatments) predicts opposition to inheritance taxes ($p < 0.01$), whereas the implemented inequalities in the self-earned context (L and M treatments) do not significantly influence tax attitudes. In China, a similar pattern emerges with some nuanced differences; there is a negative correlation between the implemented inequality in the intergenerational context and support for inheritance tax ($p < 0.05$), with no significant correlation observed in the self-earned context.

4 Discussion

Intergenerational wealth transfers, such as gifts or inheritances from parents, significantly impact wealth accumulation for younger generations at the micro-level and contribute to broader economic inequality. While much of the existing literature focuses on fairness preferences associated with self-earned wealth, our study explores fairness preferences regarding inequality caused by wealth transfers from economically advantaged parents. Through a comprehensive survey experiment conducted in the U.S. and China, we analyze perceptions of fairness in these transfers. Our findings indicate that Chinese respondents typically regard inequalities stemming from intergenerational transfers—whether the parental wealth was earned through effort or not—on par with those arising from sheer luck. Conversely, Americans strongly resist such inequalities, with a marked aversion evident regardless of the origin of wealth. Nonetheless, American respondents are more accepting of inequality from intergenerational transfer when parents' income scheme is merit-based in the first place.

These findings underscore a critical distinction between self-earned and transferred wealth, with profound implications for societal attitudes toward inequality and public policy perceptions. The marked aversion to intergenerational wealth transfers, particularly in the U.S., emphasizes the need for fairness research to further explore this domain and develop robust theories that differentiate between self-earned and intergenerational contexts more effectively. This distinction is not merely academic; it has significant implications for shaping policies that address wealth inequality.

Finally, it is important to acknowledge some limitations of our study. First, to provide clear causal evidence, our experimental design ensures that workers across treatments are perceived uniformly by spectators. However, in reality, children who receive larger transfers often possess more wealth than their peers from less affluent backgrounds, a dynamic highlighted in the literature (Feiveson and Sabelhaus, 2018). The origins of this wealth disparity are multifaceted. Wealthy parents often secure their children's early financial success through strategic educational investments, which might enhance these children's career performance. Additionally, it could be that wealthy parents provide substantial financial support, potentially reducing their children's incentive to work hard. As Andrew Carnegie famously noted, *"the parent who leaves his son enormous wealth generally deadens the talents and energies of the son, and tempts him to lead a less useful and less worthy life than he otherwise would..."* Our experimental design does not capture these nuanced details. Future studies could explore perceptions about children who receive large transfers and how these perceptions interact with fairness preferences regarding unequal intergenerational wealth transfers.

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Appendix A Additional Figures and Tables

Appendix Table A1. Background Variables for Different Treatments of the U.S. Spectator Sample

	U.S. Spectator Sample						U.S. Pop.
	M	L	MP	LP	MPN	LPN	
Demographics							
Age	48	49	50	50	49	47	48
% White	62	56	66	67	71	71	64
% Female	47	52	50	55	51	50	51
% Has at Least a 4-Year College Degree	45	42	46	48	49	47	33
% Northeast	19	24	19	20	17	17	18
% Midwest	17	16	22	21	19	19	21
% South	45	40	41	38	41	41	38
% West	20	20	18	21	23	23	23
Financial Characteristics							
% Household Income $\leq$ 50K USD	41	44	42	34	46	40	39
% Household Income 50K-100K USD	30	30	35	34	31	31	30
% Household Income 100K+ USD	30	26	24	32	32	29	31
Political affiliation					0		
% Democrat	38	38	39	35	39	36	31
% Independent	31	29	31	29	26	28	41
% Republican	24	27	26	30	29	29	28
% Prefer not to say or don't know	7	6	4	5	6	8	NA
Number of participants	471	464	455	462	490	482	

Note: This table compares the characteristics of the U.S. spectator participants with the average characteristics of the U.S. adult population. For demographics and financial characteristics, comparisons are with the 2021 American Community Survey. The political affiliations are compared to the 2023 Gallup polling results.

Appendix Table A2. Background Variables for Different Treatments of the China Spectator Sample

	China Spectator Sample						China Pop.
	M	L	MP	LP	MPN	LPN	
Demographics							
Age	40	41	39	40	36	36	42
% Han Ethnic	92	93	96	94	97	99	91
% Female	53	50	50	51	55	57	51
% Has at Least Some College Degree	60	58	62	59	76	77	17
% Tire 1 City	23	24	26	27	44	44	6
% Tire 2 City and Below	77	76	74	73	56	56	94
Financial Characteristics							
% Household Income $\leq$ 120K CNY	64	68	70	70	48	49	80
% Household Income 120K+ CNY	37	32	30	30	52	52	20
Number of participants	480	462	429	450	449	443	

Note: This table compares the characteristics of the China spectator participants with the average characteristics of the China adult population. For demographics and financial characteristics, comparisons are with the 2020 Seventh National Population Census.

Appendix Table A3. Full Regression Results on U.S. Spectator Decisions

	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.568***	0.575***	0.487***	0.184***	0.180***	0.162***	0.130***	0.131***	0.111***
	(0.100)	(0.101)	(0.110)	(0.028)	(0.028)	(0.030)	(0.026)	(0.026)	(0.028)
MP	-0.217*	-0.191*	-0.241**	-0.055*	-0.048	-0.055	-0.036	-0.026	-0.057*
	(0.114)	(0.114)	(0.120)	(0.032)	(0.032)	(0.034)	(0.029)	(0.029)	(0.031)
LP	-0.463***	-0.447***	-0.573***	-0.144***	-0.141***	-0.164***	-0.116***	-0.107***	-0.130***
	(0.112)	(0.113)	(0.123)	(0.032)	(0.032)	(0.034)	(0.029)	(0.030)	(0.031)
Age		0.001	0.001		-0.001	-0.001		-0.000	0.000
		(0.003)	(0.003)		(0.001)	(0.001)		(0.001)	(0.001)
White		-0.174**	-0.191**		-0.052**	-0.054**		-0.060***	-0.064***
		(0.089)	(0.095)		(0.025)	(0.027)		(0.023)	(0.025)
Female		-0.076	-0.047		-0.050**	-0.046*		-0.065***	-0.064***
		(0.078)	(0.084)		(0.022)	(0.023)		(0.020)	(0.022)
College		-0.023	0.007		0.004	0.016		-0.027	-0.020
		(0.087)	(0.094)		(0.025)	(0.027)		(0.023)	(0.025)
Income $\leq$ 50k		-0.201*	-0.211*		-0.083***	-0.072**		-0.057**	-0.047
		(0.107)	(0.118)		(0.030)	(0.034)		(0.028)	(0.031)
Income 50k–100k		-0.135	-0.135		-0.067**	-0.050		-0.054**	-0.044
		(0.101)	(0.111)		(0.029)	(0.031)		(0.027)	(0.029)
Northeast		0.126	0.138		0.008	0.015		0.023	0.025
		(0.105)	(0.112)		(0.029)	(0.031)		(0.027)	(0.028)
Midwest		-0.053	-0.044		-0.008	-0.015		-0.037	-0.027
		(0.106)	(0.116)		(0.030)	(0.032)		(0.027)	(0.029)
West		-0.189*	-0.176		-0.061**	-0.069**		-0.054*	-0.063**
		(0.107)	(0.114)		(0.030)	(0.032)		(0.028)	(0.030)
Democrat		-0.088	-0.088		-0.027	-0.030		-0.049*	-0.055**
		(0.099)	(0.106)		(0.029)	(0.031)		(0.026)	(0.028)
Independent		0.030	0.026		-0.013	-0.013		0.004	0.004
		(0.106)	(0.117)		(0.029)	(0.032)		(0.027)	(0.029)
Prefer not to say or don't know		0.096	0.167		0.012	0.031		-0.005	-0.009
		(0.180)	(0.180)		(0.052)	(0.052)		(0.048)	(0.050)
Constant	4.496***	4.768***	4.820***	0.649***	0.840***	0.836***	0.609***	0.761***	0.771***
	(0.078)	(0.194)	(0.206)	(0.022)	(0.055)	(0.057)	(0.020)	(0.050)	(0.053)
R-squared	0.052	0.060	0.064	0.063	0.079	0.081	0.042	0.062	0.065
N	1,852	1,852	1,852	1,852	1,852	1,852	1,852	1,852	1,852
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |\text{income of worker A} - \text{income of worker B}|/\text{total income}$. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", and "LP" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, and luck-parent treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A4. Full Regression Results on Chinese Spectator Decisions

	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.297***	0.271***	0.278*	0.113***	0.109***	0.136***	0.084***	0.077***	0.085**
	(0.101)	(0.100)	(0.142)	(0.027)	(0.027)	(0.038)	(0.025)	(0.024)	(0.033)
MP	0.045	0.049	0.257*	-0.015	-0.014	0.056	0.022	0.026	0.076**
	(0.109)	(0.109)	(0.152)	(0.030)	(0.031)	(0.042)	(0.027)	(0.027)	(0.037)
LP	-0.065	-0.056	0.149	-0.023	-0.022	0.060	0.004	0.006	0.060*
	(0.109)	(0.108)	(0.145)	(0.030)	(0.030)	(0.040)	(0.027)	(0.026)	(0.035)
Age		-0.006*	-0.003		-0.001	-0.000		-0.002**	-0.000
		(0.004)	(0.004)		(0.001)	(0.001)		(0.001)	(0.001)
Han Ethnic		0.270	0.065		0.101**	0.060		-0.066**	-0.090**
		(0.181)	(0.221)		(0.044)	(0.053)		(0.033)	(0.040)
Female		0.231***	0.295***		0.062***	0.074**		0.039**	0.018
		(0.076)	(0.108)		(0.021)	(0.029)		(0.019)	(0.025)
College		-0.071	-0.055		-0.034	-0.028		-0.027	-0.020
		(0.089)	(0.101)		(0.024)	(0.026)		(0.021)	(0.023)
High Income		0.409***	0.572***		0.075***	0.117***		0.085***	0.143***
		(0.091)	(0.161)		(0.024)	(0.038)		(0.021)	(0.033)
Tire 1 Cities		-0.336***	-0.250*		-0.061**	-0.028		-0.089***	-0.059*
		(0.095)	(0.135)		(0.026)	(0.034)		(0.023)	(0.032)
Constant	4.580***	4.447***	4.302***	0.716***	0.642***	0.577***	0.633***	0.762***	0.681***
	(0.075)	(0.260)	(0.326)	(0.021)	(0.068)	(0.085)	(0.019)	(0.056)	(0.068)
N	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821
R-squared	0.007	0.029	0.032	0.016	0.030	0.030	0.008	0.029	0.040
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |$income of worker A $-$ income of worker B$|$/total income. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", and "LP" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, and luck-parent treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the Chinese sample include age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A5. Impact of Parental Income Sources on Spectator Decisions in M Treatment

Panel A: U.S.	Allocated Earnings to High-earner			More to Higher-earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent Merit	0.001	0.014	0.025	-0.016	-0.012	-0.006	-0.004	0.005	0.004
	(0.125)	(0.125)	(0.141)	(0.035)	(0.035)	(0.037)	(0.034)	(0.034)	(0.036)
R-squared	0.000	0.024	0.020	0.000	0.018	0.020	0.000	0.029	0.035
N	471	471	471	471	471	471	471	471	471
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Panel B: China	Allocated Earnings to High-earner			More to Higher-earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent Merit	-0.069	-0.081	0.142	-0.022	-0.025	0.003	-0.019	-0.021	0.030
	(0.096)	(0.473)	(0.626)	(0.024)	(0.116)	(0.153)	(0.023)	(0.099)	(0.128)
R-squared	0.001	0.036	0.015	0.001	0.037	0.034	0.001	0.032	0.030
N	480	480	480	480	480	480	480	480	480
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |\text{income of worker A} - \text{income of worker B}|/\text{total income}$. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Concerning explanatory variables, "Parent Merit" is an indicator variable assigned a value of 1 if the spectator's parent earned their income based on performance; it is 0 otherwise. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A6. Impact of Parental Income Sources on Spectator Decisions in L Treatment

Panel A: U.S.	Allocated Earnings to High-earner			More to Higher-earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent Merit	-0.052	-0.062	0.006	-0.007	-0.002	0.027	-0.016	-0.014	0.007
	(0.157)	(0.157)	(0.163)	(0.044)	(0.044)	(0.046)	(0.041)	(0.040)	(0.043)
R-squared	0.000	0.043	0.047	0.000	0.060	0.059	0.000	0.061	0.058
N	464	464	464	464	464	464	464	464	464
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Panel B: China	Allocated Earnings to High-earner			More to Higher-earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent Merit	-0.005	-0.018	-0.070	-0.011	-0.014	0.007	0.049	0.048	0.043
	(0.149)	(0.148)	(0.207)	(0.042)	(0.042)	(0.058)	(0.037)	(0.037)	(0.051)
R-squared	0.000	0.034	0.082	0.000	0.022	0.064	0.004	0.033	0.077
N	462	462	462	462	462	462	462	462	462
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |\text{income of worker A} - \text{income of worker B}|/\text{total income}$. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Concerning explanatory variables, "Parent Merit" is an indicator variable assigned a value of 1 if the spectator's parent earned their income based on performance; it is 0 otherwise. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A7. Differences between Countries in Earnings Allocated to High-Earners

	L		M		MP		LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
U.S.	-0.084	0.094	0.187**	0.278**	-0.346***	-0.403***	-0.483***	-0.631***
	(0.108)	(0.137)	(0.092)	(0.126)	(0.115)	(0.142)	(0.113)	(0.143)
R-2	0.001	0.001	0.018	0.018	0.014	0.014	0.032	0.032
N	926	926	951	951	884	884	912	912
Re-weighted	No	Yes	No	Yes	No	Yes	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining the earnings allocated to the higher earner. The samples are divided by treatment type, with each column's title indicating the specific outcome variable. Robust standard errors are enclosed in parentheses. (3) In terms of explanatory variables, "U.S." is an indicator variable assigned a value of 1 for American spectators and 0 for Chinese spectators. (3) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A8. Regression Results on Heterogeneity Analysis

Dependent Variable: Allocated Earnings to High-earner									
	U.S.					China			
	Republican	Income >100K USD	White	College Degree	Female	Han Ethinic	Income >240K CNY	College Degree	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.546***	0.416***	0.165	0.374***	0.331**	-0.280	0.421**	0.272	0.530**
	(0.127)	(0.130)	(0.170)	(0.143)	(0.154)	(0.508)	(0.167)	(0.169)	(0.227)
MPN	-0.074	-0.091	-0.301	-0.212	-0.167	0.096	0.357*	0.322	0.391
	(0.139)	(0.140)	(0.204)	(0.157)	(0.170)	(0.577)	(0.196)	(0.203)	(0.263)
LPN	-0.363***	-0.450***	-0.510***	-0.552***	-0.254	0.441	0.232	0.123	0.088
	(0.139)	(0.143)	(0.187)	(0.158)	(0.170)	(0.479)	(0.209)	(0.229)	(0.272)
B	0.150	-0.151	-0.365**	-0.418**	-0.245	-0.333	0.923***	0.207	0.567***
	(0.190)	(0.192)	(0.168)	(0.169)	(0.164)	(0.391)	(0.243)	(0.167)	(0.211)
B×M	-0.257	0.226	0.549**	0.355*	0.317	0.634	-0.674*	-0.009	-0.495*
	(0.252)	(0.245)	(0.222)	(0.210)	(0.216)	(0.530)	(0.345)	(0.216)	(0.298)
B×MPN	-0.027	0.054	0.375	0.415*	0.162	0.126	-0.771**	-0.662***	-0.368
	(0.263)	(0.255)	(0.250)	(0.222)	(0.231)	(0.603)	(0.352)	(0.245)	(0.331)
B×LPN	-0.023	0.266	0.260	0.576***	-0.236	-0.418	-1.115***	-0.636**	-0.171
	(0.276)	(0.261)	(0.242)	(0.223)	(0.236)	(0.517)	(0.405)	(0.267)	(0.360)
R-squared	0.046	0.046	0.050	0.050	0.050	0.030	0.037	0.032	0.030
N	1,907	1,907	1,907	1,907	1,907	1,834	1,834	1,834	1,834
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Re-weighted	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Wald-test									
M+B×M	0.288	0.642***	0.713***	0.729***	0.648***	0.354**	-0.253	0.263**	0.035
	(0.218)	(0.208)	(0.144)	(0.156)	(0.153)	(0.152)	(0.303)	(0.133)	(0.190)
MPN+B×MPN	-0.101	-0.037	0.074	0.203	-0.005	0.222	-0.414	-0.340**	0.023
	(0.225)	(0.215)	(0.147)	(0.161)	(0.161)	(0.176)	(0.298)	(0.145)	(0.209)
LPN+B×LPN	-0386	-0.184	-0.250	-0.024*	-0.490***	0.022	-0.882**	0.531***	-0.083
	(0.238)	(0.219)	(0.155)	(0.159)	(0.166)	(0.190)	(0.355)	(0.148)	(0.245)

Note: (1) This table presents the results of robust OLS regressions that analyze the earnings allocated to the higher earner. Robust standard errors are detailed in parentheses. (2) The explanatory variables include "M", "MPN", and "LPN", which are indicator variables set to 1 for participants in the merit, merit-parent-no-choice, and luck-parent-no-choice treatments, respectively. "L" (luck) treatment serves as the reference category. Additionally, we consider interactions with subgroups, denoted by the indicator variable "B", which is set to 1 for participants belonging to specific subgroups identified in the column titles. All background variables from the main regression are included, except for those represented by "B". (3) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A9. Regression Results on Spectator Decisions by Excluding Spectators Who Allocated Less than 3 Points to Higher-Earner

Panel A: U.S.									
	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.440***	0.442***	0.374***	0.168***	0.165***	0.148***	0.147***	0.147***	0.125***
	(0.082)	(0.082)	(0.088)	(0.027)	(0.027)	(0.029)	(0.027)	(0.027)	(0.029)
MP	-0.125	-0.084	-0.171*	-0.040	-0.029	-0.039	-0.042	-0.028	-0.057*
	(0.093)	(0.092)	(0.099)	(0.032)	(0.032)	(0.034)	(0.031)	(0.031)	(0.033)
LP	-0.403***	-0.370***	-0.452***	-0.142***	-0.135***	-0.151***	-0.134***	-0.123***	-0.151***
	(0.093)	(0.092)	(0.098)	(0.033)	(0.033)	(0.035)	(0.031)	(0.031)	(0.033)
MPN	-0.077	-0.046	-0.107	-0.022	-0.022	-0.035	-0.026	-0.015	-0.036
	(0.090)	(0.090)	(0.097)	(0.031)	(0.031)	(0.033)	(0.030)	(0.030)	(0.032)
LPN	-0.278***	-0.253***	-0.325***	-0.084***	-0.083***	-0.096***	-0.093***	-0.084***	-0.108***
	(0.091)	(0.090)	(0.097)	(0.032)	(0.032)	(0.034)	(0.030)	(0.030)	(0.032)
R-squared	0.040	0.063	0.064	0.043	0.071	0.069	0.040	0.063	0.064
N	2,630	2,630	2,630	2,630	2,630	2,630	2,630	2,630	2,630
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Panel B: China									
	Allocated Earnings to High-Earner			More to Higher-Earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.278***	0.262***	0.294***	0.114***	0.112***	0.147***	0.093***	0.087***	0.098***
	(0.079)	(0.078)	(0.110)	(0.025)	(0.025)	(0.035)	(0.026)	(0.026)	(0.037)
MP	0.080	0.093	0.214*	-0.008	-0.006	0.042	0.027	0.031	0.071*
	(0.088)	(0.088)	(0.124)	(0.029)	(0.029)	(0.042)	(0.029)	(0.029)	(0.041)
LP	0.023	0.027	0.208*	-0.004	-0.004	0.075*	0.008	0.009	0.069*
	(0.087)	(0.086)	(0.116)	(0.029)	(0.029)	(0.039)	(0.029)	(0.029)	(0.039)
MPN	-0.047	-0.031	0.093	-0.025	-0.023	-0.004	-0.016	-0.010	0.031
	(0.087)	(0.089)	(0.143)	(0.029)	(0.030)	(0.048)	(0.029)	(0.030)	(0.048)
LPN	-0.120	-0.093	0.094	-0.056*	-0.052*	-0.025	-0.040	-0.031	0.031
	(0.089)	(0.091)	(0.146)	(0.030)	(0.031)	(0.050)	(0.030)	(0.030)	(0.049)
R-squared	0.011	0.023	0.035	0.018	0.021	0.030	0.011	0.023	0.035
N	2,468	2,468	2,468	2,468	2,468	2,468	2,468	2,468	2,468
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |$income of worker A $-$ income of worker B$|/$total income. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", "LP", "MPN", and "LPN" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, luck-parent treatment, merit-parent-no-choice treatment, and luck-parent-no-choice treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A10. Treatment Variations in the Likelihood of Allocating More to Low-earner

Dependent Variable: Whether Allocated More Earnings to Low-earner						
	U.S.			China		
	(1)	(2)	(3)	(4)	(5)	(6)
M	-0.031**	-0.030**	-0.028*	-0.010	-0.009	-0.003
	(0.014)	(0.015)	(0.016)	(0.018)	(0.018)	(0.027)
MP	0.028	0.031*	0.024	0.009	0.011	-0.022
	(0.018)	(0.018)	(0.018)	(0.020)	(0.019)	(0.026)
LP	0.022	0.026	0.039*	0.025	0.026	0.007
	(0.018)	(0.018)	(0.020)	(0.020)	(0.020)	(0.028)
MPN	-0.010	-0.007	-0.005	-0.013	0.004	-0.033
	(0.016)	(0.016)	(0.017)	(0.018)	(0.019)	(0.025)
LPN	0.004	0.006	0.014	-0.001	0.020	0.027
	(0.016)	(0.017)	(0.018)	(0.019)	(0.020)	(0.036)
R-squared	0.006	0.012	0.013	0.002	0.031	0.035
N	2,824	2,824	2,824	2,713	2,713	2,713
Controls	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining whether the likelihood that the spectator allocates more earnings to the low earner varies across treatments. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", "LP", "MPN", and "LPN" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, luck-parent treatment, merit-parent-no-choice treatment, and luck-parent-no-choice treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

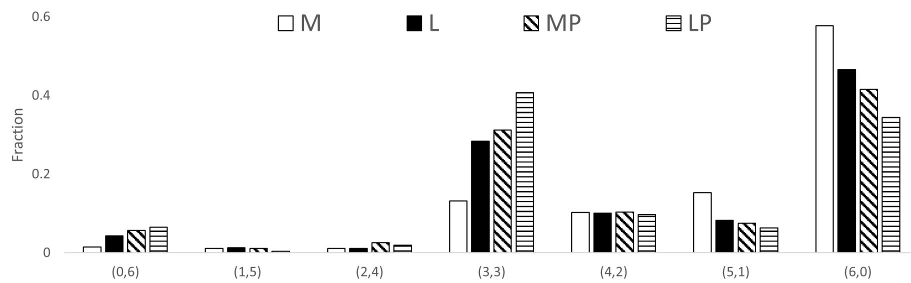
Appendix Table A11. Policy preferences: Support or Against inheritance tax

	U.S./Against		China/Support	
	Intergenerational	Self-made	Intergenerational	Self-made
	(1)	(2)	(3)	(4)
Allocated Earnings to High-earner	0.027***	-0.001	-0.020**	-0.015
	(0.007)	(0.011)	(0.010)	(0.010)
Age	0.008***	0.008***	-0.000	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
White/Han	0.073***	0.078**	0.014	0.069*
	(0.028)	(0.038)	(0.062)	(0.036)
Female	0.041*	0.047	0.011	0.025
	(0.024)	(0.034)	(0.024)	(0.024)
Has at Least a 4-Year College Degree	-0.133***	-0.088**	0.041	0.068**
	(0.027)	(0.039)	(0.030)	(0.028)
Income $\leq$ 50k USD	-0.057*	-0.004		
	(0.034)	(0.048)		
Income 50k–100k USD	0.037	0.066		
	(0.032)	(0.046)		
Income $>$240K CHY			0.111***	0.036
			(0.039)	(0.031)
Tire 1 Cities			0.025	0.044
			(0.028)	(0.041)
Northeast	0.034	0.081*		
	(0.033)	(0.045)		
Midwest	0.080**	0.015		
	(0.032)	(0.048)		
West	0.027	0.002		
	(0.031)	(0.045)		
Republican	0.145***	0.088**		
	(0.027)	(0.041)		
Constant	-0.146**	-0.086	0.290***	0.074
	(0.058)	(0.083)	(0.085)	(0.078)
R-squared	0.129	0.113	0.071	0.041
Observations	1889.000	935.000	1771.000	942.000
Weighted	Yes	Yes	Yes	Yes

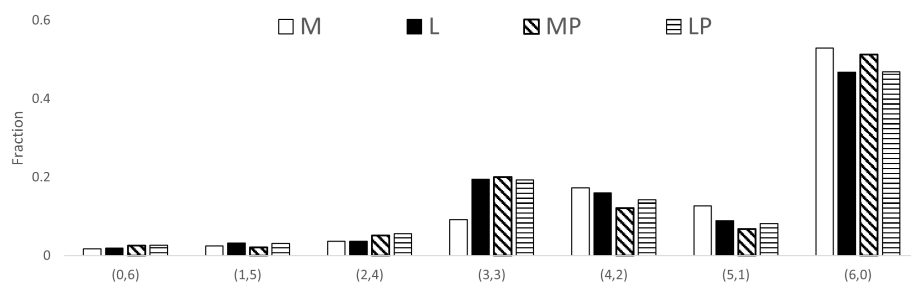
Note: (1) This table displays the outcomes of robust OLS regressions examining the correlation between spectators' policy preference and their allocation choices. and (2) For the U.S. sample, the dependent variable is the dummy variable indicating whether the spectator is strongly against inheritance tax. For the China sample, the dependent variable is the dummy variable, indicating whether spectators strongly favor inheritance tax. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Figure A1: Distribution of Spectator Choices

(a) U.S.



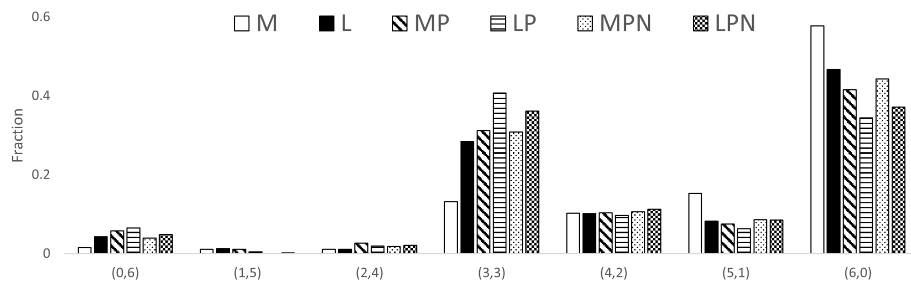
(b) China



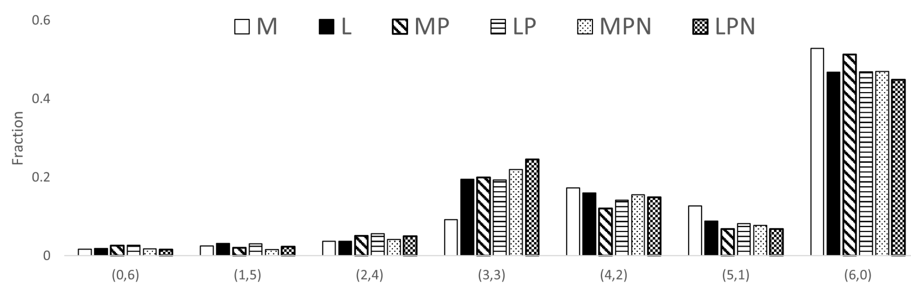
Note: This figure illustrates the distribution of spectator decisions by American and Chinese participants across four treatment groups. The x-axis choices (x, y) represent earnings allocations, where x indicates the earnings allocated to the lower earner and y denotes the earnings allocated to the higher earner.

Appendix Figure A2: Distribution of Spectator Choices for All Treatments

(a) U.S.



(b) China



Note: This figure illustrates the distribution of spectator decisions by American and Chinese participants across six treatment groups. The x-axis choices (x, y) represent earnings allocations, where x indicates the earnings allocated to the lower earner and y denotes the earnings allocated to the higher earner.

Appendix B Heterogeneous Analysis: Self-Earned vs. Parent-Determined Transfers

In this section, We explore heterogeneity in fairness preferences across the U.S. and China using comprehensive background data collected through our survey, with the exception of location specifics. In the U.S., our analysis focuses on variables such as political orientation, household income level, race, education level, and gender. In China, the focus shifts to ethnicity, household income, education level, and gender. This heterogeneity is examined through the following regression for each background variable:

$$\begin{aligned} y_i = \alpha + \alpha_M M_i + \alpha_{MP} MP_i + \alpha_{LP} LP_i + \alpha^B B_i + \alpha_M^B M_i \times B_i + \\ \alpha_{MP}^B MP_i \times B_i + \alpha_{ML}^B ML_i \times B_i + \gamma \mathbf{X}_i + \varepsilon_i \end{aligned} \tag{3}$$

Here, B_i represents an indicator variable for whether spectator i belongs to the subgroup specified in the column title. In this model, $\mathbf{X}_i$ encompasses all background variables, excluding the variable represented by B_i. This regression includes interactions between the background indicator and treatment indicators, such as $B_i \times M_i$, $B_i \times MP_i$, and $B_i \times LP_i$.

Table B1 displays the weighted estimated results, adjusted to national representative samples. The focus is on whether treatment effects observed in Table 2 are consistent across different subgroups. For example, coefficients of $M + B \times M$, $MP + B \times MP$, and $ML + B \times ML$ reveal the treatment effects for participant subgroups like Republicans, households income over 100K USD, Whites, college graduates, and females. Conversely, coefficients of M, MP, and LP provide estimated treatment effects for their respective counterpart subgroups.

We begin our analysis with the U.S. sample. The effects of the M treatment and LP treatment are notably consistent across subgroups. Specifically, replacing luck with merit as the source of inequality results in a significant increase in inequality acceptance across all subgroups ($p < 0.01$ in all cases, except for non-white and republicans). Conversely, replacing luck with wealth transferred from a lucky parent significantly decreases inequality acceptance across most subgroups (except households with income larger than 100K).

Appendix Table B1. Regression Results on Heterogeneity Analysis

Dependent Variable: Allocated Earnings to High-earner									
	U.S.					China			
	Republican	Income >100K USD	White	College Degree	Female	Han Ethinic	Income >240K CNY	College Degree	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.556***	0.420***	0.142	0.383***	0.321**	-0.278	0.421**	0.269	0.540**
	(0.127)	(0.130)	(0.169)	(0.143)	(0.155)	(0.502)	(0.167)	(0.170)	(0.227)
MP	-0.186	-0.394***	-0.489**	-0.476***	-0.357**	-0.277	0.434**	0.342*	0.447*
	(0.139)	(0.139)	(0.191)	(0.155)	(0.171)	(0.512)	(0.170)	(0.180)	(0.236)
LP	-0.542***	-0.688***	-0.616***	-0.789***	-0.673***	0.138	0.169	0.219	0.306
	(0.146)	(0.148)	(0.196)	(0.162)	(0.185)	(0.536)	(0.172)	(0.171)	(0.229)
B	0.151	-0.135	-0.475***	-0.444***	-0.233	-0.261	0.945***	0.168	0.579***
	(0.191)	(0.194)	(0.170)	(0.170)	(0.165)	(0.389)	(0.244)	(0.164)	(0.209)
B×M	-0.249	0.252	0.593***	0.350*	0.334	0.624	-0.665*	-0.015	-0.526*
	(0.252)	(0.245)	(0.222)	(0.211)	(0.217)	(0.524)	(0.347)	(0.215)	(0.297)
B×MP	-0.201	0.580**	0.428*	0.753***	0.221	0.595	-0.994**	-0.553**	-0.362
	(0.275)	(0.272)	(0.246)	(0.230)	(0.236)	(0.538)	(0.418)	(0.236)	(0.310)
B×LP	-0.093	0.406	0.107	0.684***	0.189	0.040	0.154	-0.370	-0.263
	(0.273)	(0.266)	(0.253)	(0.233)	(0.245)	(0.559)	(0.285)	(0.226)	(0.301)
R-squared	0.063	0.066	0.068	0.070	0.065	0.035	0.043	0.035	0.036
N	1,852	1,852	1,852	1,852	1,852	1,821	1,821	1,821	1,821
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Re-weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald-test									
M+B×M	0.308	0.672***	0.735***	0.733***	0.654***	0.345**	-0.243	0.254**	0.014
	(0.218)	(0.208)	(0.144)	(0.156)	(0.153)	(0.153)	(0.305)	(0.132)	(0.190)
MP+B×MP	-0.387	0.187	-0.061	0.277	-0.135	0.318*	-0.560	-0.211	0.085
	(0.238)	(0.236)	(0.156)	(0.171)	(0.166)	(0.164)	(0.382)	(0.153)	(0.203)
LP+B×LP	-0.635***	-0.282	-0.510***	-0.106*	-0.484***	0.178	0.322	-0.151	0.043
	(0.231)	(0.222)	(0.159)	(0.168)	(0.163)	(0.156)	(0.226)	(0.148)	(0.194)

Note: (1) This table presents the results of robust OLS regressions that analyze the earnings allocated to the higher earner. Robust standard errors are detailed in parentheses. (2) The explanatory variables include "M", "MP", and "LP", which are indicator variables set to 1 for participants in the merit, merit-parent, and luck-parent treatments, respectively. "L" (luck) treatment serves as the reference category. Additionally, we consider interactions with subgroups, denoted by the indicator variable "B", which is set to 1 for participants belonging to specific subgroups identified in the column titles. All background variables from the main regression are included, except for those represented by "B". (3) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Turning to the China sample, the causal effect of replacing luck with merit as the source of inequality shows no significant impact among females, wealthy individuals with household incomes over 240K CNY, college educated, and minorities. Consistent with the main findings, most subgroups do not differentiate between inequality derived from luck or wealth transfers, regardless of the parents' means of acquiring their wealth.

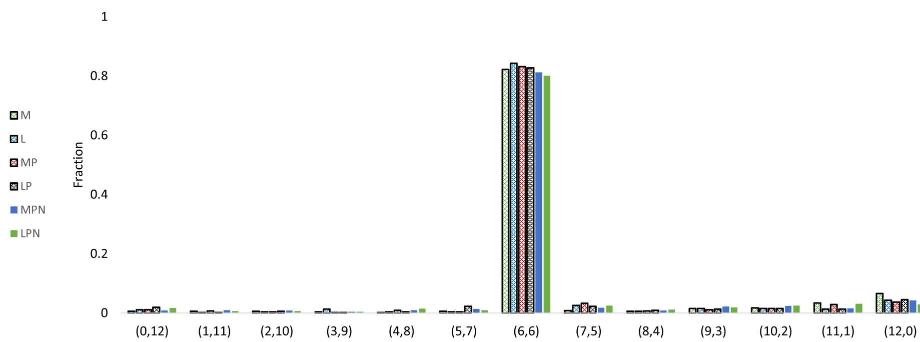
Appendix C Analysis When Both Workers Had 6 Initial Earnings

In this section, we examine how spectators distributed total earnings when each worker started with initial earnings of 6 points. When two workers are equally positioned initially, as in this scenario, it is reasonable to expect spectators to allocate 6 points to each worker. This expectation aligns with common fairness norms, including egalitarianism, meritocracy, and libertarianism.

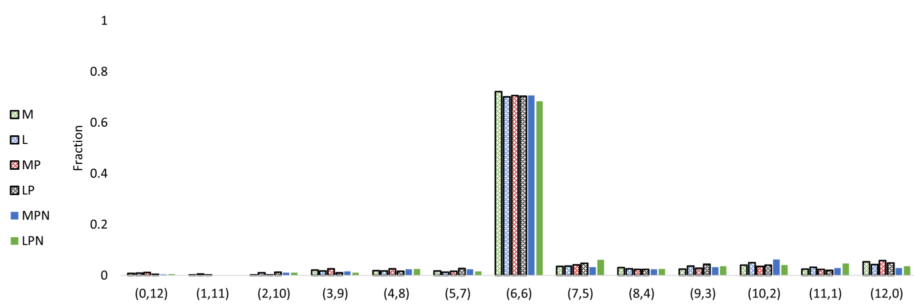
Descriptive Analysis Figure C1 illustrates the specific allocation choices. More than 80% of American spectators distributed earnings equally between workers, and over 70% of Chinese spectators did the same. Nonetheless, a minority of spectators choose various unequal distributions even when workers began with identical initial earnings.

Appendix Figure C1: Distribution of Spectator Choices When the Initial Income of Both Workers Is 6

(a) U.S.



(b) China



Note: This figure illustrates the distribution of spectator decisions by American and Chinese participants across four treatment groups. The x-axis choices (x, y) represent earnings allocations, where x indicates the earnings allocated to the lower earner and y denotes the earnings allocated to the higher earner.

Regression Analysis To determine if the likelihood of choosing an equal split remains consistent across different treatments, we conducted a robust OLS regression:

$$y_i = \alpha + \alpha_M M_i + \alpha_{MP} MP_i + \alpha_{LP} LP_i + \gamma \mathbf{X}_i + \varepsilon_i \tag{4}$$

In this model, y_i is a dummy variable indicating whether the spectator opts for an equal distribution, i.e., (6,6). The variables M_i, MP_i, and LP_i indicate whether spectator i was in the Merit, Merit-Parent, or Luck-Parent treatment, respectively, with the Luck treatment serving as the reference category. These estimates are interpreted relative to this baseline.

Analysis was conducted separately for American and Chinese samples. The vector $\mathbf{X}_i$ includes control variables such as age, gender, race, census region, education level, household income, and political affiliation for the U.S., and age, gender, ethnicity, education level, household income, and city tier level for China. Results from regressions both with and without these control variables are presented.

Table C1 displays the regression results for both the U.S. and China samples, showing a similar propensity for equal earning distribution across treatments.

Finally, to address potential concerns that subjects who chose non-(6,6) allocations may have misunderstood the experiment instructions or selected allocations at random, we excluded these potentially low-quality responses and repeated the analysis in Table 2. The findings, detailed in Table C2, are consistent with our main results, reinforcing the robustness of our conclusions.

Appendix Table C1. Regression Analysis of Whether the Spectator Chooses (6,6) When Initial Income of Both Workers is Set at 6

	U.S.			China		
	(1)	(2)	(3)	(4)	(5)	(6)
M	-0.021	-0.019	-0.021	0.020	0.017	0.020
	(0.024)	(0.024)	(0.026)	(0.030)	(0.030)	(0.042)
MP	-0.012	-0.020	-0.014	0.005	0.002	0.059
	(0.024)	(0.024)	(0.026)	(0.031)	(0.031)	(0.044)
LP	-0.016	-0.028	-0.035	0.003	0.000	0.043
	(0.024)	(0.024)	(0.027)	(0.030)	(0.030)	(0.042)
MPN	-0.030	-0.030	-0.018	0.005	-0.021	-0.031
	(0.024)	(0.024)	(0.026)	(0.030)	(0.031)	(0.050)
LPN	-0.042*	-0.042*	-0.039	-0.017	-0.043	-0.019
	(0.025)	(0.025)	(0.027)	(0.031)	(0.031)	(0.050)
R-squared	0.001	0.047	0.044	0.001	0.006	0.010
Observations	2,824	2,824	2,824	2,713	2,713	2,713
Controls	No	Yes	Yes	No	Yes	Yes
Weighted	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining whether spectator chooses (6,6) when the initial income of both workers is 6. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", "LP", "MPN", and "LPN" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, luck-parent treatment, merit-parent-no-choice treatment, and luck-parent-no-choice treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table C2. Regression Results on Spectator Decisions for Unequal Scenario: Only Including Spectators Who Choose (6,6) When Initial Income of Both Workers is Set at 6

Panel A: U.S.									
	Allocated Earnings to High-earner			More to Higher-earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.617***	0.616***	0.499***	0.216***	0.213***	0.187***	0.160***	0.161***	0.137***
	(0.100)	(0.100)	(0.109)	(0.029)	(0.029)	(0.031)	(0.029)	(0.029)	(0.030)
MP	-0.269**	-0.232*	-0.340***	-0.078**	-0.068**	-0.088**	-0.043	-0.030	-0.068*
	(0.120)	(0.120)	(0.126)	(0.035)	(0.035)	(0.037)	(0.033)	(0.033)	(0.035)
LP	-0.623***	-0.601***	-0.748***	-0.194***	-0.190***	-0.224***	-0.156***	-0.145***	-0.176***
	(0.118)	(0.119)	(0.128)	(0.035)	(0.035)	(0.037)	(0.033)	(0.033)	(0.035)
MPN	-0.004	0.003	-0.076	-0.009	-0.012	-0.026	-0.034	-0.028	-0.044
	(0.110)	(0.110)	(0.117)	(0.034)	(0.034)	(0.036)	(0.032)	(0.032)	(0.034)
LPN	-0.264**	-0.256**	-0.382***	-0.092***	-0.095***	-0.117***	-0.103***	-0.095***	-0.119***
	(0.113)	(0.113)	(0.122)	(0.035)	(0.035)	(0.037)	(0.033)	(0.033)	(0.035)
R-squared	0.037	0.045	0.047	0.044	0.062	0.062	0.032	0.053	0.054
N	2824.000	2824.000	2824.000	2824.000	2824.000	2824.000	2824.000	2824.000	2824.000
Controls	1,852	1,852	1,852	1,852	1,852	1,852	1,852	1,852	1,852
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes
Panel B: China									
	Allocated Earnings to High-earner			More to Higher-earner			Implemented Inequality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
M	0.219**	0.210**	0.247*	0.115***	0.114***	0.134***	0.078***	0.077***	0.081**
	(0.103)	(0.102)	(0.146)	(0.028)	(0.028)	(0.037)	(0.029)	(0.028)	(0.037)
MP	0.074	0.107	0.332**	0.002	0.008	0.067	0.018	0.027	0.063
	(0.111)	(0.111)	(0.145)	(0.033)	(0.033)	(0.044)	(0.033)	(0.033)	(0.043)
LP	-0.053	-0.049	0.049	-0.017	-0.017	0.023	-0.011	-0.009	0.015
	(0.112)	(0.111)	(0.155)	(0.033)	(0.033)	(0.044)	(0.032)	(0.032)	(0.042)
MPN	0.041	0.117	0.360**	0.017	0.040	0.076	0.006	0.027	0.082*
	(0.108)	(0.110)	(0.156)	(0.032)	(0.033)	(0.047)	(0.032)	(0.033)	(0.047)
LPN	-0.111	-0.039	0.142	-0.031	-0.009	0.017	-0.032	-0.011	0.050
	(0.114)	(0.117)	(0.194)	(0.034)	(0.035)	(0.053)	(0.033)	(0.034)	(0.050)
R-squared	0.006	0.018	0.039	0.015	0.022	0.034	0.008	0.020	0.041
N	1,910	1,910	1,910	1,910	1,910	1,910	1,910	1,910	1,910
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Re-weighted	No	No	Yes	No	No	Yes	No	No	Yes

Note: (1) This table displays the outcomes of robust OLS regressions examining three variables: the earnings allocated to the higher earner, a dummy variable indicating whether the spectator allocates more earnings to the higher earner, and the implemented inequality, defined as $e_i = |\text{income of worker A} - \text{income of worker B}|/\text{total income}$. Column titles indicate the outcome variables. Robust standard errors are in parentheses. (2) Regarding explanatory variables, "M", "MP", "LP", "MPN", and "LPN" are indicator variables taking the value 1 if the spectator is in the merit treatment, merit-parent treatment, luck-parent treatment, merit-parent-no-choice treatment, and luck-parent-no-choice treatment respectively. The reference category for these regressions is the "L" (luck) treatment. (3) Control variables for the U.S. sample include age, race, gender, education, household income, region, and political affiliation. For the Chinese sample, the controls are age, ethnic status (whether Han ethnic), gender, education, household income, and city tier level. (4) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix D Survey Instruments for Spectator

General Information

Welcome! This is an academic study on decision-making conducted by researchers.

<u>Procedures</u>

This study takes approximately 10 minutes, and participation is voluntary. You may drop out of this study at any time with no penalties or consequences of any kind. You are only allowed to participate in this study once.

<u>Confidentiality</u>

The collected data in this study will be used only for research purposes and shared in anonymized form in open science repositories in ways that will not reveal who you are. No one will be able to identify you from the shared data.

<u>Questions</u>

If you have questions about this study or if you have a research-related problem, you may contact the researchers at kelinluecon@gmail.com.

<u>Consent</u>

By participating in this study, you indicate that you are 18 years of age or older, that you understand the above information, and that you voluntarily agree to participate in this study.

Do you consent to these terms?

- o No
- o Yes

[[Submit]]

The next question is about the following problem. In questionnaires like ours, sometimes there are participants who do not carefully read the questions and just quickly click through the survey. This compromises the results of research studies. To show that you are reading the survey carefully, please choose both "Very strongly interested" and "Not at all interested" as your answer to the next question.

Given the above, how interested are you in football?

Very strongly interested

Very interested

A little bit interested

Not very interested

Not at all interested

[[Submit

Unlike the usual questionnaires that ask you about hypothetical scenarios, **here, your decisions will impact real people in real-life situations**. Please read the following page carefully. A quiz will test your understanding. You can proceed with the study only if you answer all quiz questions correctly.

Background Information

We recruited lots of college students and their parents to join our study. **To verify their relationship, we asked parents to present an official ID, which we then cross-checked with the student's enrollment records.** Students and their parents are guaranteed a fixed participation payment, and there's a chance to earn extra money based on what they decide during the study.

Students take part in the study in a college classroom without internet access. At the same time, their parents are in a different place doing their part. **They can't talk to each other or know what the other is doing.**

【M treatment and parents' income is also determined by merit】

Parent Decisions

Parents first worked on a quiz. After they finished, **we told parents that their income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's how it worked: if their performance is above the median level, they earned 15 points; if not, they got nothing. Therefore, 50% of the parents earned 15 points, while the other 50% earned none. Points will be transferred to actual money to their bank account by a fixed ratio.

Your Role in This Study:

Students also worked on the quiz assignment. Once the assignments are completed, **we pair students up. Let us consider two such paired students, whom we'll call Student A and Student B.**

Once the assignment was completed, **we told students that their initial income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's what you need to know about how payment works: if their performance is above the median level, they would earn 6 points and, otherwise, nothing. Therefore, 50% of them earned 6 points, while the other 50% earned none.

These points will be turned into money on the student's school card. Students can spend this money at college.

We didn't tell Student the outcome of their initial earnings. However, we told them they were paired with another student, and their combined income will be pooled. Then, selected individuals (like you) will decide to redistribute the total income, ultimately determining the students' final payoff.

You are one of the third person, and we now want **you to choose whether to redistribute the total income earned from the assignment performance between Student A and Student B.** Your decision has a 10% chance (one out of ten) of determining their final income allocation.

Your decision is completely anonymous. The students will receive the final and will not receive any further information.

Your Choices:

Before You Decide: There are **three possible outcomes for Student A and Student B's total income decided by the assignment performance.**

- They could either both earn 6 points,
- one could earn 6 points while the other earns none,
- or they could both earn no points at all.

You'll need to think about different situations. The real situation for Student A and Student B would be one of these situations.

Please think carefully about your choices, as they will have a direct impact on the students' payoff.

Situation 1: Student A did well on the assignment and got 6 points, but Student B didn't get any points.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 0 Points.

I do redistribute:

• student A is paid 5 Points, and student B is paid 1 Point.

• student A is paid 4 Points, and student B is paid 2 Points.

• student A is paid 3 Points, and student B is paid 3 Points.

• student A is paid 2 Points, and student B is paid 4 Points.

• student A is paid 1 Point, and student B is paid 5 Points.

• student A is paid 0 Points, and student B is paid 6 Points.

Situation 2: Both Student A and Student B performed well and earned 6 points.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 6 Points.

I do redistribute:

• student A is paid 12 Points, and student B is paid 0 Points.

• student A is paid 11 Points, and student B is paid 1 Points.

• student A is paid 10 Points, and student B is paid 2 Points.

• student A is paid 9 Points, and student B is paid 3 Points.

• student A is paid 8 Points, and student B is paid 4 Points.

• student A is paid 7 Points, and student B is paid 5 Points.

• student A is paid 5 Points, and student B is paid 7 Points.

• student A is paid 4 Points, and student B is paid 8 Points.

• student A is paid 3 Points, and student B is paid 9 Points.

• student A is paid 2 Points, and student B is paid 10 Points.

• student A is paid 1 Point, and student B is paid 11 Points.

• student A is paid 0 Points, and student B is paid 12 Points.

Situation 3: **Both Student A and Student B** earn nothing. So, you do not need to make any redistribution decisions.

【L treatment and parents' income is also determined by merit】

Parent Decisions

Parents first worked on a quiz. After they finished, **we told parents that their income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's how it worked: if their performance is above the median level, they earned 15 points; if not, they got nothing. Therefore, 50% of the parents earned 15 points, while the other 50% earned none. Points will be transferred to actual money to their bank account by a fixed ratio.

Your Role in This Study:

Students also worked on a quiz assignment. Once the assignments are completed, **we pair students up. Let us consider two such paired students, whom we'll call Student A and Student B.**

Once the assignment was completed, **we told students that their initial income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's what you need to know about how payment works: Their initial earnings will be based on a lottery, not the quiz performance. 50% of workers randomly win a lottery and receive 6 points each, while the rest receive none

These points will be turned into money on the student's school card. Students can spend this money at college.

We didn't tell Student the outcome of their initial earnings. However, we told them they were paired with another student, and their combined income will be pooled. Then, selected individuals (like you) will decide to redistribute the total income, ultimately determining the students' final payoff.

You are one of the third person, and we now want **you to choose whether to redistribute the total income earned from the random lottery between Student A and Student B.** Your decision has a 10% chance (one out of ten) of determining their final income allocation.

Your decision is completely anonymous. The students will receive the final and will not receive any further information.

Your Choices:

Before You Decide: There are **three possible outcomes for Student A and Student B's total income decided by the random lottery.**

- They could either both earn 6 points,
- one could earn 6 points while the other earns none,
- or they could both earn no points at all.

You'll need to think about different situations. The real situation for Student A and Student B would be one of these situations.

Please think carefully about your choices, as they will have a direct impact on the students' payoff.

Situation 1: By luck, Student A also won the lottery, getting 6 points, while Student B didn't win anything.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 0 Points.

I do redistribute:

• student A is paid 5 Points, and student B is paid 1 Point.

• student A is paid 4 Points, and student B is paid 2 Points.

• student A is paid 3 Points, and student B is paid 3 Points.

• student A is paid 2 Points, and student B is paid 4 Points.

• student A is paid 1 Point, and student B is paid 5 Points.

• student A is paid 0 Points, and student B is paid 6 Points.

Situation 2: Both Student A and Student B win the lottery and earn 6 points by luck.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 6 Points.

I do redistribute:

• student A is paid 12 Points, and student B is paid 0 Points.

• student A is paid 11 Points, and student B is paid 1 Points.

• student A is paid 10 Points, and student B is paid 2 Points.

• student A is paid 9 Points, and student B is paid 3 Points.

• student A is paid 8 Points, and student B is paid 4 Points.

• student A is paid 7 Points, and student B is paid 5 Points.

• student A is paid 5 Points, and student B is paid 7 Points.

• student A is paid 4 Points, and student B is paid 8 Points.

• student A is paid 3 Points, and student B is paid 9 Points.

• student A is paid 2 Points, and student B is paid 10 Points.

• student A is paid 1 Point, and student B is paid 11 Points.

• student A is paid 0 Points, and student B is paid 12 Points.

Situation 3: **Both Student A and Student B** earn nothing. So, you do not need to make any redistribution decisions.

【MP treatment】

Parent Decisions

Parents first worked on a quiz. After they finished, **we told parents that their income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's how it worked: if their performance is above the median level, they earned 15 points; if not, they got nothing. Therefore, 50% of the parents earned 15 points, while the other 50% earned none. Points will be transferred to actual money to their bank account by a fixed ratio.

[choice]

If parents earned 15 points, we asked if they would like to transfer 6 points out of 15 to their child. We explained that this transfer would determine their child's payment, although other factors might also affect the final payment. Parents who did not earn any points could not transfer funds to their children.

[no-choice]

For parents who earned 15 points, we told them we would transfer 6 points out of 15 to their child, and they would keep the remaining 9 points. We explained that this transfer would determine their child's payment, although other factors might also affect the final payment. Parents who did not earn any points could not transfer funds to their children.

These points will be turned into money on the student's school card. Students can spend this money at college, but it can't be turned back into cash. We told the parents that their kids wouldn't know what choice they made, and the transfer was completely anonymous.

Your Role in This Study:

Students also worked on a quiz assignment. Once the assignments are completed, **we pair students up. Let us consider two such paired students, whom we'll call Student A and Student B.**

Once the assignment was completed, **we told students that their initial income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's what you need to know about how payment works: **Earnings are not based on quiz performance. Instead, earnings depend on whether a student's parent leaves income to them. If a parent leaves income, the student receives 6 points; otherwise, they receive no points.**

These points will be turned into money on the student's school card. Students can spend this money at college.

We didn't tell Student the outcome of their initial earnings. However, we told them they were paired with another student, and their combined income will be pooled. Then, selected individuals (like you) will decide to redistribute the total income, ultimately determining the students' final payoff.

You are one of the third person, and we now want **you to choose whether to redistribute the total income earned from their own parent between Student A and Student B.** Your decision has a 10% chance (one out of ten) of determining their final income allocation.

Your decision is completely anonymous. The students will receive the final and will not receive any further information.

Your Choices:

Before You Decide: There are **three possible outcomes for Student A and Student B's total income determined by their own parent.**

- They could either both earn 6 points,
- one could earn 6 points while the other earns none,
- or they could both earn no points at all.

You'll need to think about different situations. The real situation for Student A and Student B would be one of these situations.

Please think carefully about your choices, as they will have a direct impact on the students' payoff.

Situation 1: Student A received 6 points from their parent, and Student B got none from theirs.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 0 Points.

I do redistribute:

• student A is paid 5 Points, and student B is paid 1 Point.

• student A is paid 4 Points, and student B is paid 2 Points.

• student A is paid 3 Points, and student B is paid 3 Points.

• student A is paid 2 Points, and student B is paid 4 Points.

• student A is paid 1 Point, and student B is paid 5 Points.

• student A is paid 0 Points, and student B is paid 6 Points.

Situation 2: Both Student A and Student B get 6 points from their own parents.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 6 Points.

I do redistribute:

• student A is paid 12 Points, and student B is paid 0 Points.

• student A is paid 11 Points, and student B is paid 1 Points.

• student A is paid 10 Points, and student B is paid 2 Points.

• student A is paid 9 Points, and student B is paid 3 Points.

• student A is paid 8 Points, and student B is paid 4 Points.

• student A is paid 7 Points, and student B is paid 5 Points.

• student A is paid 5 Points, and student B is paid 7 Points.

• student A is paid 4 Points, and student B is paid 8 Points.

• student A is paid 3 Points, and student B is paid 9 Points.

• student A is paid 2 Points, and student B is paid 10 Points.

• student A is paid 1 Point, and student B is paid 11 Points.

• student A is paid 0 Points, and student B is paid 12 Points.

Situation 3: **Both Student A and Student B** earn nothing. So, you do not need to make any redistribution decisions.

【M treatment and parents' income is also determined by luck】

Parent Decisions

Parents first worked on a quiz. After they finished, **we told parents that their income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's how it worked: Their initial earnings will be based on a lottery, not the quiz performance. 50% of parents randomly win a lottery and receive 15 points each, while the rest receive none. Points will be transferred to actual money to their bank account by a fixed ratio.

Your Role in This Study:

Students also worked on a quiz assignment. Once the assignments are completed, **we pair students up. Let us consider two such paired students, whom we'll call Student A and Student B.**

Once the assignment was completed, **we told students that their initial income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's what you need to know about how payment works: if their performance is above the median level, they would earn 6 points and, otherwise, nothing. Therefore, 50% of them earned 6 points, while the other 50% earned none.

These points will be turned into money on the student's school card. Students can spend this money at college.

We didn't tell Student the outcome of their initial earnings. However, we told them they were paired with another student, and their combined income will be pooled. Then, selected individuals (like you) will decide to redistribute the total income, ultimately determining the students' final payoff.

You are one of the third person, and we now want **you to choose whether to redistribute the total income earned from the assignment performance between Student A and Student B.** Your decision has a 10% chance (one out of ten) of determining their final income allocation.

Your decision is completely anonymous. The students will receive the final and will not receive any further information.

Your Choices:

Before You Decide: There are **three possible outcomes for Student A and Student B's total income decided by the assignment performance.**

- They could either both earn 6 points,
- one could earn 6 points while the other earns none,
- or they could both earn no points at all.

You'll need to think about different situations. The real situation for Student A and Student B would be one of these situations.

Please think carefully about your choices, as they will have a direct impact on the students' payoff.

Situation 1: Student A did well on the assignment and got 6 points, but Student B didn't get any points.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 0 Points.

I do redistribute:

• student A is paid 5 Points, and student B is paid 1 Point.

• student A is paid 4 Points, and student B is paid 2 Points.

• student A is paid 3 Points, and student B is paid 3 Points.

• student A is paid 2 Points, and student B is paid 4 Points.

• student A is paid 1 Point, and student B is paid 5 Points.

• student A is paid 0 Points, and student B is paid 6 Points.

Situation 2: Both Student A and Student B performed well and earned 6 points.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 6 Points.

I do redistribute:

• student A is paid 12 Points, and student B is paid 0 Points.

• student A is paid 11 Points, and student B is paid 1 Points.

• student A is paid 10 Points, and student B is paid 2 Points.

• student A is paid 9 Points, and student B is paid 3 Points.

• student A is paid 8 Points, and student B is paid 4 Points.

• student A is paid 7 Points, and student B is paid 5 Points.

• student A is paid 5 Points, and student B is paid 7 Points.

• student A is paid 4 Points, and student B is paid 8 Points.

• student A is paid 3 Points, and student B is paid 9 Points.

• student A is paid 2 Points, and student B is paid 10 Points.

• student A is paid 1 Point, and student B is paid 11 Points.

• student A is paid 0 Points, and student B is paid 12 Points.

Situation 3: **Both Student A and Student B** earn nothing. So, you do not need to make any redistribution decisions.

【L treatment and parents' income is also determined by luck】

Parent Decisions

Parents first worked on a quiz. After they finished , **we told parents that their income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's how it worked: Their initial earnings will be based on a lottery, not the quiz performance. 50% of parents randomly win a lottery and receive 15 points each, while the rest receive none. Points will be transferred to actual money to their bank account by a fixed ratio.

Your Role in This Study:

Students also worked on a quiz assignment. Once the assignments are completed, **we pair students up. Let us consider two such paired students, whom we'll call Student A and Student B.**

Once the assignment was completed, **we told students that their initial income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's what you need to know about how payment works: Their initial earnings will be based on a lottery, not the quiz performance. 50% of workers randomly win a lottery and receive 6 points each, while the rest receive none.

These points will be turned into money on the student's school card. Students can spend this money at college.

We didn't tell Student the outcome of their initial earnings. However, we told them they were paired with another student, and their combined income will be pooled. Then, selected individuals (like you) will decide to redistribute the total income, ultimately determining the students' final payoff.

You are one of the third person, and we now want **you to choose whether to redistribute the total income earned from the random lottery between Student A and Student B.** Your decision has a 10% chance (one out of ten) of determining their final income allocation.

Your decision is completely anonymous. The students will receive the final and will not receive any further information.

Your Choices:

Before You Decide: There are **three possible outcomes for Student A and Student B's total income decided by the random lottery.**

- They could either both earn 6 points,
- one could earn 6 points while the other earns none,
- or they could both earn no points at all.

You'll need to think about different situations. The real situation for Student A and Student B would be one of these situations.

Please think carefully about your choices, as they will have a direct impact on the students' payoff.

Situation 1: By luck, Student A also won the lottery, getting 6 points, while Student B didn't win anything.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 0 Points.

I do redistribute:

• student A is paid 5 Points, and student B is paid 1 Point.

• student A is paid 4 Points, and student B is paid 2 Points.

• student A is paid 3 Points, and student B is paid 3 Points.

• student A is paid 2 Points, and student B is paid 4 Points.

• student A is paid 1 Point, and student B is paid 5 Points.

• student A is paid 0 Points, and student B is paid 6 Points.

Situation 2: Both Student A and Student B win the lottery and earn 6 points by luck.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 6 Points.

I do redistribute:

• student A is paid 12 Points, and student B is paid 0 Points.

• student A is paid 11 Points, and student B is paid 1 Points.

• student A is paid 10 Points, and student B is paid 2 Points.

• student A is paid 9 Points, and student B is paid 3 Points.

• student A is paid 8 Points, and student B is paid 4 Points.

• student A is paid 7 Points, and student B is paid 5 Points.

• student A is paid 5 Points, and student B is paid 7 Points.

• student A is paid 4 Points, and student B is paid 8 Points.

• student A is paid 3 Points, and student B is paid 9 Points.

• student A is paid 2 Points, and student B is paid 10 Points.

• student A is paid 1 Point, and student B is paid 11 Points.

• student A is paid 0 Points, and student B is paid 12 Points.

Situation 3: **Both Student A and Student B** earn nothing. So, you do not need to make any redistribution decisions.

【LP treatment】

Parent Decisions

Parents first worked on a quiz. After they finished, **we told parents that their income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's how it worked: Their initial earnings will be based on a lottery, not the quiz performance. **50% of parents randomly win a lottery and receive 15 points each, while the rest receive none. Points will be transferred to actual money to their bank account by a fixed ratio.**

[choice]

If parents earned 15 points, we asked if they would like to transfer 6 points out of 15 to their child. We explained that this transfer would determine their child’s payment, although other factors might also affect the final payment. Parents who did not earn any points could not transfer funds to their children.

[no-choice]

For parents who earned 15 points, we told them we would transfer 6 points out of 15 to their child, and they would keep the remaining 9 points. We explained that this transfer would determine their child’s payment, although other factors might also affect the final payment. Parents who did not earn any points could not transfer funds to their children.

These points will be turned into money on the student's school card. Students can spend this money at college, but it can't be turned back into cash. We told the parents that their kids wouldn't know what choice they made, and the transfer was completely anonymous.

Your Role in This Study:

Students also worked on a quiz assignment. Once the assignments are completed, **we pair students up. Let us consider two such paired students, whom we'll call Student A and Student B.**

Once the assignment was completed, **we told students that their initial income would be based on a predetermined set of payment rules. But, we didn't share what these rules were exactly**. Here's what you need to know about how payment works: **Earnings are not based on quiz performance. Instead, earnings depend on whether a student’s parent leaves income to them. If a parent leaves income, the student receives 6 points; otherwise, they receive no points.**

These points will be turned into money on the student's school card. Students can spend this money at college.

We didn't tell Student the outcome of their initial earnings. However, we told them they were paired with another student, and their combined income will be pooled. Then, selected individuals (like you) will decide to redistribute the total income, ultimately determining the students' final payoff.

You are one of the third person, and we now want **you to choose whether to redistribute the total income earned from their own parent between Student A and Student B.** Your decision has a 10% chance (one out of ten) of determining their final income allocation.

Your decision is completely anonymous. The students will receive the final and will not receive any further information.

Your Choices:

Before You Decide: There are **three possible outcomes for Student A and Student B's total income determined by their own parent.**

- They could either both earn 6 points,
- one could earn 6 points while the other earns none,
- or they could both earn no points at all.

You'll need to think about different situations. The real situation for Student A and Student B would be one of these situations.

Please think carefully about your choices, as they will have a direct impact on the students' payoff.

Situation 1: Student A received 6 points from their parent, and Student B got none from theirs.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 0 Points.

I do redistribute:

• student A is paid 5 Points, and student B is paid 1 Point.

• student A is paid 4 Points, and student B is paid 2 Points.

• student A is paid 3 Points, and student B is paid 3 Points.

• student A is paid 2 Points, and student B is paid 4 Points.

• student A is paid 1 Point, and student B is paid 5 Points.

• student A is paid 0 Points, and student B is paid 6 Points.

Situation 2: Both Student A and Student B get 6 points from their own parents.

Please state which of the following alternatives you choose:

I do not redistribute:

• student A is paid 6 Points, and student B is paid 6 Points.

I do redistribute:

• student A is paid 12 Points, and student B is paid 0 Points.

• student A is paid 11 Points, and student B is paid 1 Points.

• student A is paid 10 Points, and student B is paid 2 Points.

• student A is paid 9 Points, and student B is paid 3 Points.

• student A is paid 8 Points, and student B is paid 4 Points.

• student A is paid 7 Points, and student B is paid 5 Points.

• student A is paid 5 Points, and student B is paid 7 Points.

• student A is paid 4 Points, and student B is paid 8 Points.

• student A is paid 3 Points, and student B is paid 9 Points.

• student A is paid 2 Points, and student B is paid 10 Points.

• student A is paid 1 Point, and student B is paid 11 Points.

• student A is paid 0 Points, and student B is paid 12 Points.

Situation 3: **Both Student A and Student B** earn nothing. So, you do not need to make any redistribution decisions.

Open Box

We would like to know your thoughts on how to redistribute the payoff between student A and student B, **especially when they started with different earnings (0 and 6 points).**

Your response is valuable for this research project. Therefore, please take the time to respond carefully and in several sentences if needed.

Demographic for US sample

What is your current age? Please enter a number.

What is your gender?

o Male (1)

o Female (2)

o Non-binary / third gender (3)

Please choose one or more races that you consider yourself to be: Please select all that apply.

▢ White (1)

▢ Black or African American (2)

▢ American Indian or Alaska Native (3)

▢ Asian (4)

▢ Native Hawaiian or Other Pacific Islander (5)

▢ Other, please specify: (6) ____

What is the highest level of school you have completed, or the highest degree you have received?

o Less than high school (1)

o High school diploma (or equivalent) (2)

o Some college but no degree (including academic, vocational, or occupational programs) (3)

o Associate/Junior College degree (including academic, vocational, or occupational programs) (4)

o Bachelor's Degree (For example: BA, BS) (5)

o Master's Degree (For example: MA, MBA, MS, MSW) (6)

o Doctoral Degree (For example: PhD) (7)

o Professional Degree (For example: MD, JD, DDS) (8)

Generally speaking, do your political preferences lean Republican, Democrat, or Independent?

o Republican (1)

o Democrat (2)

o Independent (3)

o Prefer not to say or don't know (4)

In which state is your primary residence?

Which category represents the total combined pre-tax income of all members of your household (including you) during over the last year?

Please include money from all jobs, net income from the business, farm or rent, pensions, interest on savings or bonds, dividends, social security income, unemployment benefits, food stamps, workers compensation or disability benefits, child support, alimony, scholarships, fellowships, grants, inheritances and gifts, and any other money income received by members of your household who are 15 years of age or older.

o Less than $10,000 (1) $10,000 to $19,999 (2)

o $20,000 to $29,999 (3)

o $30,000 to $39,999 (4)

o $40,000 to $49,999 (5)

o $50,000 to $59,999 (6)

o $60,000 to $74,999 (7)

o $75,000 to $99,999 (8)

o $100,000 to $149,999 (9)

o $150,000 to $199,999 (10)

o $200,000 or more (11)

Have you ever received or do you think you might have gotten any inheritance from your parents or others?

o Yes, I've received or expect to get an inheritance.

o No, I haven't received it and don't expect to get any inheritance.

Could you please estimate the value of the inheritance you've received or anticipate receiving?

o Under $10,000

o $10,000 to $50,000

o $50,001 to $100,000

o $100,001 to $500,000

o Over $500,000

Do you plan to leave an inheritance to your child(ren)?

o Yes, I plan to leave a bequest.

o I'm considering it, but I haven't decided yet.

o No, I do not plan to leave a bequest.

o I have not considered it.

An inheritance tax is a fee charged on the assets received by individuals from someone who has passed away. How do you feel about the implementation of an inheritance tax?

o Strongly in favor

o Somewhat in favor

o Neutral / No opinion

o Somewhat against

o Strongly against

Appendix E Instruction for Worker

[Translated from Chinese]

Please read the instructions below carefully.

General Instructions:

We are academic researchers from Huazhong University of Science and Technology. The results from this experiment will be used for a research project, so it is important to read and follow all instructions carefully. Your participation will remain anonymous. We will use only your college ID to assign payments. Once we verify that your parent has correctly entered your college ID and completed their part of the study, you will receive a fixed participation fee of 30 RMB. Additionally, depending on the actions you and others take, you may earn extra money. Your parents will also be compensated for their participation. Neither you nor your parents will know each other's actions during the experiment.

In this study, you will complete 4 assignments. Each assignment includes 8 logic and math questions, and you will have 4 minutes to complete each one. Your performance on each assignment may affect your additional earnings. You have a maximum of 4 minutes to complete each assignment.

Questions:

If you have any questions about this study or encounter any research-related issues, you may contact the researchers at 2023010220@hust.educ.cn.

Consent:

By participating in this study, you confirm that you are 18 years of age or older, that you understand the above information, and that you voluntarily agree to participate in this study. You also agree to provide your college ID numbers for verification.

Do you consent to these terms?

- o No

- o Yes

[[Submit]]

Assignments 1-4

Some question examples:

One day, a customer came to Harlan's store, selected goods worth 25 yuan, and gave Harlan a 100 yuan bill. Harlan didn’t have enough change, so he went to the next store, exchanged the 100 yuan for change, and gave the customer 75 yuan in change. Later, the neighbor came back saying the 100 yuan was counterfeit, and Harlan replaced it with a genuine bill. How much did Harlan lose?

Answer: 100

A pasture is known to be able to feed 27 cows for 6 days before the grass is completely consumed; 23 cows can be fed for 9 days. How many days can the pasture feed 21 cows, given the grass keeps growing?

Answer: 12

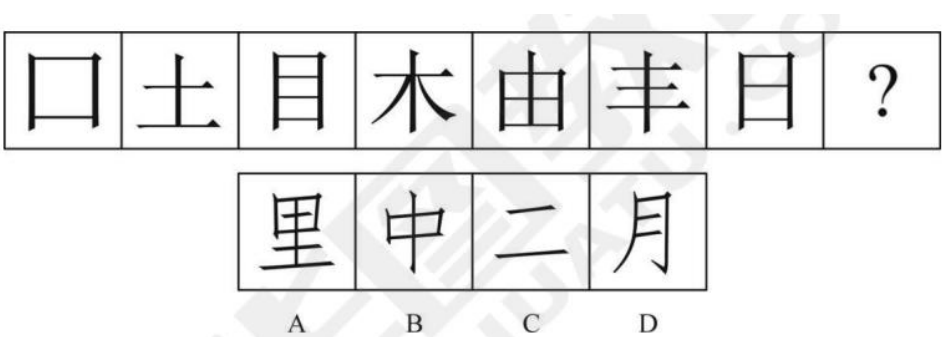
In 24 hours, how many times do the hour, minute, and second hands of a clock align completely?

Answer: 2

Sequence: 1, 1, 2, 3, 5, 8, ... What is the next number?

Answer: 13

Choose the most appropriate option from the given four options to fill in the blank to show a certain pattern.



Answer: D

……

Payoff Determination:

For each assignment, your payment will be determined by a predetermined rule. Afterward, a randomly selected third party will have the opportunity to redistribute the earnings between you and another participant. This third party will not know your identity or that of the other participant, but they will be informed about the nature of the assignment and your respective earnings.

You will receive payments for all four assignments plus your participation fee. The money will be transferred to your college card.

Appendix F Instruction for Parent

[Translated from Chinese]

Please read the instructions below carefully.

General Instructions:

We are academic researchers from Huazhong University of Science and Technology. The results from this experiment will be used in a research project. It is important that you carefully read and follow all instructions. Your participation will remain anonymous. Once you complete the study, you will receive a fixed participation fee of 30 RMB. Depending on the actions you and others take during the experiment, you may also earn additional money.

Questions:

If you have any questions about this study or encounter any research-related issues, please contact the researchers at 2023010220@hust.edu.cn.

Consent:

By participating in this study, you confirm that you are 18 years of age or older, that you understand the information provided above, and that you voluntarily agree to participate in this study.

Do you consent to participate in this study?

- No

- Yes

[Submit]

Relationship Verification

As your child may have already informed you, they are also participating in this study simultaneously at their school. Neither you nor your child will know what the other is doing during the experiment. Your child will receive their payment once we verify that you (the parent) are also participating in the experiment.

- Please enter your child's college ID below:
  ____

- Now, please upload a picture of the relevant page from your Hukou booklet. We will immediately delete the picture after verifying the information with your child's student enrollment record at school.

Task Instructions

In this study, you will need to complete 4 assignments. Each assignment consists of 8 questions involving logic and mathematics. You will have a maximum of 4 minutes to complete each assignment. Your performance on these assignments may determine your additional payoff.

Assignments are the same with Workers.

[Add Assignment here]

Payoff Determination

Luck:

For each assignment, your payment will be determined by a random lottery with a 50% chance of winning 15 points. Otherwise, you will receive 0 points. Each point is equivalent to 1 CNY.

Merit:

For each assignment, your payment will be based on your performance. If your performance is above the median, you will earn 15 points; otherwise, you will receive 0 points. Each point is equivalent to 1 CNY.

Transfer

For each assignment, if you earn 15 points, we would ask you whether you would like to transfer 6 of your points to your child. This transfer will determine your child's earnings from their assignment. Please note that while your decision to transfer points is crucial, other factors will also play a role in determining the final amount your child receives. Your child will not be aware of your decisions, and your choice will remain anonymous. The points you transfer, along with those earned by your child, will be converted into funds on their college card, which can only be used within the college and cannot be converted to cash.

- Would you choose to transfer 6 points to your child if you earn 15 points?
  - No
  - Yes

Transfer no choice

For each assignment, if you earn 15 points, we will transfer 6 of your points to your child. This transfer will determine your child’s earnings from their assignment. Please note that other factors will also play a role in determining the final amount your child receives. Your child will not be aware of your transfer. The points you transfer, along with those earned by your child, will be converted into funds on their college card, which can only be used within the college and cannot be converted to cash.