ERASMUS UNIVERSITY ROTTERDAM

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Bachelor Thesis Economics and Business Economics

Genetics Determining Income

How Genetics Affect Views on Meritocratic Pay, Inequality and Redistribution

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Abstract

Inequality is a continuing relevant topic in public debate (Piketty, 2014). There are differing views on inequality. These views differ on which determinants and magnitudes of inequality are acceptable as well as how to deal with inequality (Almås et al., 2020). In general, people find inequalities stemming in higher part from luck less acceptable than inequalities stemming from more effort and less luck, as in a meritocratic reward model (Andre, 2021; Cappelen et al., 2017). Genetics are part of luck (Coop & Przeworski, 2022). This paper looks into peoples' views and preferences on inequality caused in part by luck, specifically luck in the form of genetics. Through a randomized treatment, the effects of the size of the role of genetics on redistributive preferences are assessed. This is done in a context where pay-offs are performance based. It is found that when genetics play a large role in outcomes, people are inclined to redistribute a larger amount. Performance based pay in a meritocratic model is regarded as being less fair when genetics play a large role. As a result, compensation is desired. No significant effect of mentioning genetics on distributive choices were found, although mentioning it did influence whether people considered genetics at all when distributing rewards. The fact that people prefer more redistribution when genetics play a larger role, can be used by policymakers in decision-making regarding pay-offs and for designing redistributive policies.

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1 Introduction

Inequality is an incredibly important issue in the world, with economists discussing it for centuries (Piketty, 2014). Sociologists, historians and philosophers also discuss this topic. This makes sense as everyone is affected by inequality since people observe others' ways of living and their means. Inequality is increasingly seen as a social issue that deserves attention (Atkinson, 1997). This increasing attention for inequality has various explanations, with the main one simply being an increase in inequality, especially since the 1970's (Piketty, 2014; Sen, 2000; Corry & Glyn, 1994). Other possible explanations are economic trends such as globalization of the economic structure, focus on basic (economic) rights for all people and concerns for macro-level issues in the economic context (total economic growth) (Grusky & Kanbur, 2006). Non-economic potential reasons for the increased attention are ethnic unrest and growing knowledge about the negative effects of poverty on the individual. An important source for economic inequalities are differences in incomes, with income inequality often being used as a measurement of economic inequality (Jenkins, 1991). Governments have an important role in addressing inequality. They have two channels through which income inequality can be limited: a taxation system and government expenditures/subsidies (Sen, 2000). Governments use both these channels, despite coming with potential costs of efficiency loss. In the Netherlands, the tax and subsidy system ensures that post-tax inequality is less than pre-tax inequality based on gross income (Bruil et al., 2022). This is mainly achieved by governmental spending targeting the bottom income levels in the population. With about 50% of all government expenditures going towards social benefits, the topic of inequality and redistribution is extremely relevant for the general population as well as policymakers (OECD, 2021).

Inequality is not always perceived negatively, and the views on inequality are highly dependent on the societal context (Almås et al., 2020). Sometimes inequality is regarded positively since it is the result of good performance and gives incentives to work hard. In meritocratic societies, where rewards are based on performance, inequality is more accepted (Mijs, 2021). This can be explained by the fact that in these societies inequalities are viewed as being fair since they are the result of peoples' own actions. The source of inequality forms an important factor in how people view inequalities (Cappelen et al., 2013). Inequalities due to choices such as the level of effort someone exerts, are more accepted than inequalities arising from luck, such as ex-ante differences in expected outcomes. People judge a situation to be more fair when a winner is decided based on effort rather than luck (Cappelen et al., 2017). People are more inclined to limit inequalities by redistributing rewards when they are due to external factors instead of performance-based (Drucker, 2022). Luck for an individual can stem from either genetics or external factors like social circumstances (Coop & Przeworski, 2022). Genetics as luck are a possible cause for inequalities (Harden, 2021). The topic of redistributive choices when outcomes are partly luck-based is studied increasingly. It is important with the societal impacts of redistribution policies, which is why this paper tries try to contribute to research on the topic.

This paper performs research on this topic through multiple of ways. Firstly, by using secondary data it is assessed whether the size of the role of genetics matters for peoples redistributive preferences and further beliefs. This specific factor of luck is not studied previously and gives further insight in what is regarded as being fair. It adds to existing literature on inequalities and redistribution with differing sources of inequality (Andre, 2021; Drucker, 2022; Cappelen et al., 2013). Secondly, it is assessed using primary data whether mentioning genetics affects peoples' beliefs and preferences through the perceived role of genetics. Having genetics as a factor affecting performance available in one's mind could affect its perceived role (Esgate & Groome, 2005; Tversky & Kahneman, 1973). As a result, this could affect fairness views and redistributive choices (Spiers, 2002). The second method more closely resembles how the topic would come up in real-life. Thirdly and finally, secondary pre-treatment data and primary control group data are compared to research potential differences between respondent groups with different nationalities and cultures, similar to Almås et al. (2020).

The role played by genetics is highly relevant in a social context as it could have policy implications on redistributive policies. With the advancements in the field of genetics, more knowledge on how to deal with inequalities that arise due to genetics can be used to create future policies that correspond with societal views on fairness. With this context, the central question of this paper is:

"What do people think about redistribution in a meritocratic situation and how do their beliefs and preferences change when the role of genetics is either large or small, and what is the effect of mentioning genetics?"

The remainder of this paper answers this question in the following way: Chapter 2 provides a theoretical framework to specify this question and to hypothesize on expected results. Chapter 3 describes the methodology used. Then, the results are discussed in Chapter 4, followed by the discussion of results, limitations and implications in Chapter 5. Finally, Chapter 6 presents the main conclusion and some final remarks.

2 Theoretical framework on inequalities, redistribution and luck

Inequality is a broad topic, and it has its impact all throughout society. As Mount (2009) defines equality, there are five overlapping types of equalities: political/legal equality, equality of outcome, equality of opportunity, equality of treatment and equality of membership in social groups. This paper focusses a focus on equality of outcome and equality of opportunity. Equality of outcome is defined mostly as equality of monetary outcomes, namely income and wealth. There are various theories on how to approach and handle this type of equality. Equality of opportunity refers to genetics providing differing starting positions for task performance.

Inequality and arguments against it

Inequality is prominently discussed by Kuznets (1955) who stated that income inequality as a function of income per capita automatically moves in an inverse-U shape. Piketty (2014) discusses counterexamples of this and argues that inequality should be monitored and limited by governments, with an important role for the tax system (Piketty & Saez, 2013). Inequality has been rising for the past decades (Piketty, 2014; Sen, 2000; Corry & Glyn, 1994). This rise occurs primarily through two channels: inequality in income and inequality that is maintained through inheriting of wealth (Jenkins, 1991; Piketty, 2000). With increasing economic inequalities, the topic draws more attention as well (Atkinson, 1997; Piketty, 2014; Sen, 2000). Economists argue for policies that limit inequalities, for both instrumental systemic and principal reasons. Birdsall (2001) shows that inequality can slow down both growth and poverty reduction. Additionally, it can lead to disruptions in all layers of society leading to sub-optimal decision-making by politicians. Finally, she discusses that inequality can lead to a higher level of acceptance of inequalities creating a self-fulfilling feedback loop resulting in a higher equilibrium of inequality levels in society. This is in contrast to Glaeser's (2005) work, which discusses the uncertainty of the relation between inequality (acceptance) and lower levels of redistribution, and which of these is the causes the other. Grusky and Kanbur (2006) add to Birdsall (2001) that inequality can furthermore have negative effects on individuals. This becomes apparent through negative effects in health and political involvement, as well as the inability to afford basic necessities.

With the idea of 'basic necessities', Grusky et al. (2006) allude to principal reasons against inequalities. A concern for others is not compatible with the 'classic' economic view of self-interested people as it can be the foundation to make choices for others' benefit (Charness & Rabin, 2002). These choices are the result of social preferences, where one's utility is in part derived from other peoples' payoffs and the relation between those payoffs with their own. Altruism implies that one wants to maximize others' pay-offs, either relative to or regardless of their own pay-offs (Loewenstein et al., 1989; Charness & Rabin, 2002). The presence of Rawlsian preferences, where utility is solely based on the welfare of the least wealthy person, egalitarian preferences and, in some cases, utilitarian preferences can explain an attitude against inequalities (Charness & Rabin, 2002; Loewenstein et al., 1989). What is considered 'fair' depends in a large way on those social preferences. Besides preferences on outcomes, also preferences on opportunities are important. Sen (1977) is one of the most impactful economists that argues against the idea of self-interest. He states that decisions should be made on the basis of morality. His ideas can be linked to equality of opportunity as Mount (2009) identified.

Inequality acceptance and redistribution

Based on the aforementioned, it may seem that inequality is always unwanted. Yet practice shows otherwise. Similar to social preferences, the extent of inequality acceptance differs between cultures. The United States has a much higher level of inequality than Scandinavian countries, and preferences there also present a higher desired level of inequalities (Almås et al., 2020). Inequalities are often accepted through the idea of meritocracy: "a social system in which advancement in society is based on an individual's capabilities and merits rather than on the basis of family, wealth, or social background" (Kim & Choi, 2017). Results and payoffs should be based on abilities and actions instead of social background or luck (Grant, 2018). Mijs (2021) notes that income inequality is rising, and so do peoples' acceptance levels of inequality. He states that this could be because of rising beliefs in a meritocratic system, in which inequalities that arise are deserved. Furthermore he notes that in more unequal societies, citizens are more likely to explain differences by a meritocratic process, thus justifying the differences. As a result, there will be a lower demand for redistribution. Similar to Glaeser (2005), Mijs (2021) describes the relationship between inequalities and (the demand for) redistribution to be mutually influential. As inequality is explained more by a meritocratic process, other factors such as familial wealth and connections are discounted further (Mijs, 2021). Disregarding these non-meritocratic factors might correspond with reality, as inequalities are heavily persisted by non-meritocratic factors (Piketty, 2000). Wealth inequalities are for a large part due to familial transmission of wealth through inheritances, leading to a concentration of wealth as a result of initial inequalities (Piketty, 2014). Familial ambitions and having the freedom to efficiently increase productivity due to available wealth also increase inequality (Piketty, 2000). Societal factors contributing to inequality are credit constraints and local segregation limiting connections. Finally, behavioral factors play a role; self-fulfilling beliefs which lead to aspiration failure or poverty traps make overcoming inequality more difficult (Duflo et al., 2011; Dalton et al., 2016).

Inequalities arise due to a variety of factors, some of which are meritocratic. Besides cultural differences, another important component that influences peoples' views on fairness of inequalities is the source of the inequality (Cappelen et al., 2013). When outcomes are determined by luck, this is perceived as less fair and gives reason for redistribution (Cappelen et al., 2017; Almås et al., 2020). In previous experiments people were found to compensate for unequal ex ante possible outcomes (Capellen et al., 2013). Differences occurred due to choices made, generally gave no reason to redistribute. This shows the importance respondents in that experiment gave to equality of opportunity. People are more inclined to limit inequalities by redistributing rewards when inequalities are due to external factors instead of performance-based (Drucker, 2022). People do not always redistribute rationally in accordance to meritocratic fairness, where rewards are given in proportion to merit (Andre, 2021). Capellen et al. (2017) found a 'merit primacy effect', an inconsistency in fairness views where people redistributed most when merit determined most of outcomes. This compared to similar (lower) redistribution amounts when outcomes were either fully or only 10% merit based.

Besides the general rule that people try to distribute in a way that matches performance, further research has been done on situations including more ambiguous roles for performance and luck. Andre (2021) found that people did not compensate an externally disadvantaged person only when no information was provided about what the disadvantaged person would have done otherwise. This puts the 'burden of doubt' on the disadvantaged worker. These irrationalities have to be considered when deciding on policies. Drucker (2022) found similar to Capellen et al. (2013) that people compensate for ex ante differences due to externalities, but added that they do not compensate for ex ante differences in abilities. In real-life vignettes, it was found that when part of outcomes are due to effort as well as external circumstances (race, social background), people do not redistribute (Andre, 2021). This conflicts with the idea of meritocratic fairness where external circumstances are compensated for. There are also different interpretations of merit, as choices and motivation are also highly linked with familial ties and upbringing. All things considered, people view inequalities due to luck as being more unfair, and therefore need to be compensated. These views are quite persistent, but irrationality occurs, especially in cases where the cause of inequalities is unclear.

Genetics as being part of luck

With the role of luck being detrimental to peoples' perception on the fairness of rewards, this role of luck forms an interesting topic for research. To add to prior research, this paper discusses differences in fairness views with a specific type of luck, that can either be seen as pure luck, but also as being part of talent: genetics (Andre, 2021). Luck is a combination of genetics and (social) circumstances (Coop & Przeworski, 2022). Both these sources of luck can lead to immense differences in educational attainment and income (Harden, 2021; Harden 2022). Harden (2021) emphasizes that genetics are due to chance, can lead to inequalities and should be considered in policy decisions. Since peoples' fairness views might differ between genetics and 'luck' in the broad sense, there is a gap in literature that this paper will discuss. Genetics affect many life outcomes. Some biological outcomes like blood type are fully determined by genetics (Willoughby et al., 2019). Behavioral outcomes, however, are affected by environmental factors as well as genetics (Gericke et al., 2017; Harden, 2022). Theories on how genetics affect behavioral/social outcomes has transformed from a one-on-one causal model, to a multifactorial model, where many genes combined with a myriad of environmental factors together determine the outcome (Gericke et al., 2017). Genetic determinism is the belief that outcomes are, to a larger extent than in reality, predetermined by genetics. This can have negative social consequences as genetic determinism can give cause for discrimination on race, gender or other factors. Gericke et al. (2017) found surprising evidence that people had low beliefs of genetic determination for social traits, and also that knowledge of genetics had a low correlation with beliefs of genetic determination. They say to teach people about the effect genetics can have on social traits through a more philosophical rather than purely biological lens. Harden (2022) also stated the importance of using information about the role of genetics for policy-making. Learning about the role of genetics can affect how people view their control on outcomes, which in turn affects their behavior. An example of this in the context of genetics influencing obesity is discussed by Dar-Nimrod et al. (2014).

The role of genetics is difficult to attribute causally, considering the multifactorial model that shows that many factors influence outcomes (Gericke et al., 2017). Since it is difficult to express genes causally, there is another measure used for this: heritability (Willoughby et al., 2019). Heritability is defined within the field of genetics and behavioral genetics as the ratio or percentage in which the variation of the phenotype (behavior, outwardly expressed) can be explained by variation in genotype (genetics, internally determined) (Visscher et al., 2008). This assumes that variation in phenotype can be explained by variation in genotype and variation in environmental factors. While heritability is a useful metric, there are some common misconceptions. The main one is that people wrongfully interpret it causally as the percentage of a phenotype that is genetic, rather than the percentage of the variance in phenotype (Wray & Visscher, 2008; Visscher et al., 2008). Heritability is not necessarily constant. It can change when environmental factors change (better school system), the genetic composition of a population changes (natural selection, inbreeding, introduction of new genes in a population), or when the correlation between genes and the environment changes (Wray & Visscher, 2008). Despite the fact that the concept of heritability does not seem very intuitive, Willoughby et al. (2019) have shown that in general people were quite good at intuitively estimating heritability in ways that the lay estimate corresponded to heritability found in large scale studies. This proves that heritability can be used as a measure to express the role of genetics for certain traits, but the complexity of the concept should be considered when interpreting results.

Contributions

This paper will look into peoples' beliefs and preferences on fairness in situations where luck and merit are combined. To contribute to the existing literature, the focus will be on situations where luck is specified as the role that genetics plays. This will provide further knowledge on acceptance of inequality, views on inequalities resulting from genetical differences, views about meritocracy and redistributive preferences. Given that peoples' perception about fairness is not always consistent and can differ based on framing, it is necessary to split up the broader concept of luck (Capellen et al., 2017; Andre, 2021). Redistributive choices and fairness views of people will first be studied in situations where genetics are said (to respondents) to play either a large role or a small role. This allows measurement of whether people believe that redistribution is more desired when the role of genetics as being part of luck is larger. Based primarily on the works of Cappelen et al. (2017) and Almås et al. (2020) the hypothesis is that in situations where respondents are told that mathematical ability has a high heritability, they are more likely to redistribute. That is because genetics are partly luck (Coop & Przeworski, 2022), so people are expected to argue that the loser should be compensated for a (probable) disadvantage in the task. To contribute further, the effect of simply mentioning genetics on redistributive choices and perceived fairness is studied. Spiers (2002) discusses concepts being more present in one's mind can lead to inductive thinking, leading to different decisions/views than would otherwise be the case. This can be linked to the availability heuristic, which generally states that people might overestimate the frequency or probability of an event based on how readily it comes to mind (Tversky & Kahneman, 1973; Colman, 2015). It can also be used in the context of importance, where people might think that a concept must be important since they have it readily available in their mind (Esgate & Groome, 2005). It is expected that people who just were reminded of genetics playing (some) role in outcomes, are likely to estimate the effect of genetics as being larger than those who are not reminded of genetics. Because of this, people who were presented with genetics as influencing outcomes are expected to redistribute more as a way to compensate inequalities that arise from luck, in this case genetics.

With the current advancements in the field of genetics (Cheng et al., 2022), genetics will be more present in considerations. Hence, having information on what (redistributive) policies are desired is increasingly important. Harden (2022) further discusses the relevance of behavior genetics as being a political science. She mentioned that changing how people think about the role of genetics and fairness can have large policy implications. She argues that knowledge about which inequalities to accept and which to limit in a world where people differ is of essential importance to create fair, sustainable policy. For designing redistributive policies, knowledge on peoples' perception on the topic is relevant.

3 Methodology

The analysis in this paper consists of analysis of secondary data (from here on: survey A) and primary data (from here on: survey B). These surveys are related to their own dataset, methodology, analysis, results and discussion, which are also indicated with either A or B.

3.1 Methodology A

For this paper, dataset A is used for a more general analysis on peoples' views in a situation in which they might redistribute, in situations with either a large or small role of genetics, in the form of heritability. Dataset A uses data from Pogliano (2024). Distribution of survey A was completed January 15th and 16th by Andrea Pogliano. A total of 850 individuals in the United States of America were recruited via Prolific and completed the survey, with 340 workers (combined into 170 pairs) and 510 spectators. All participating individuals were compensated by a combination of a flat rate fee ($1.25 for workers and $2.50 for spectators) and a bonus that could be achieved ($6 dollar bonus per worker pair and up to $0.50 for spectators). Workers had to answer ten mathematical questions. Spectators were provided with information about a worker pair and who won, then had to make a redistributive choice about the bonus of the worker, along with some additional questions. The analysis will focus on the spectators (respondents). Spectators were equally divided into two treatment groups: LowGen and HighGen. An attention check was failed by 35 respondents (6.86% of total respondents), these respondents were excluded in the analysis. The resulting dataset consisted of 475 respondents, 241 of which were appointed to LowGen, 234 to HighGen.

Outcome variables and survey flow

The survey flows of both survey A and B are depicted in figure 1. For a full overview of variables and how they differ between surveys, see Appendix A.

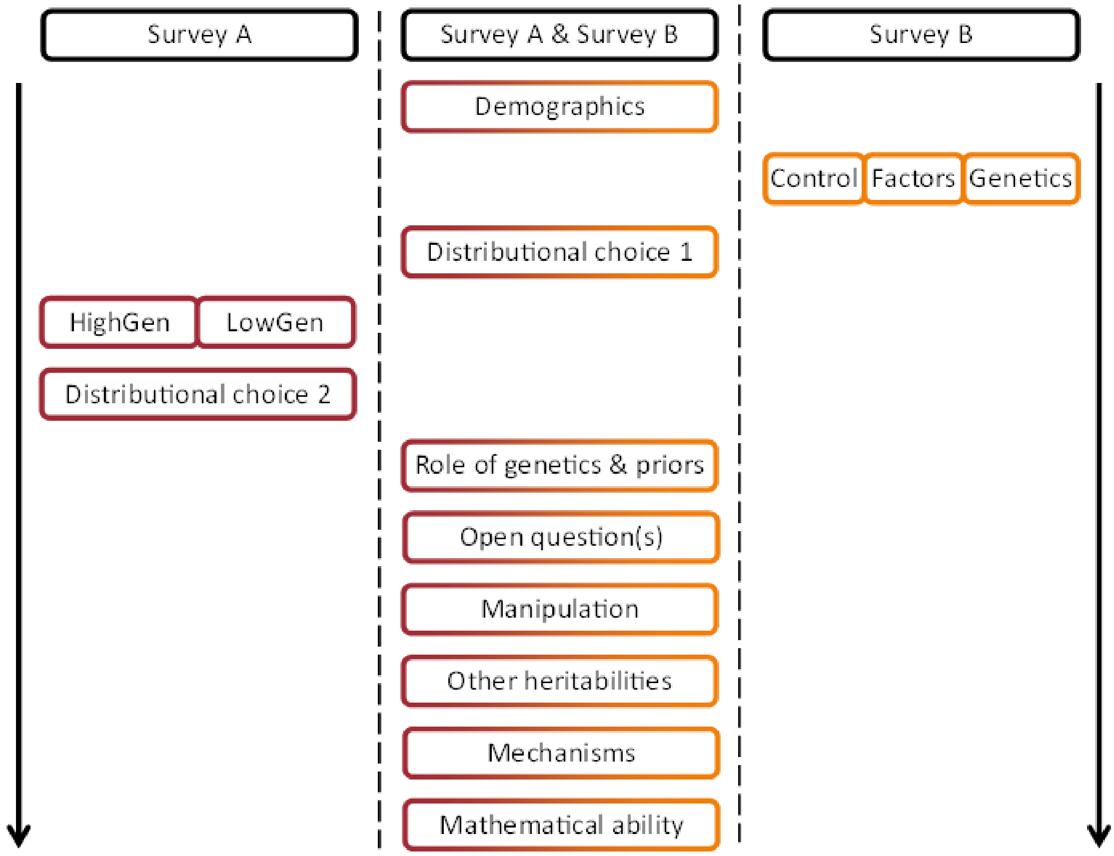

Figure 1 Survey flows Survey A and Survey B - Left column shows treatment groups and variable types only applicable in survey A, right column shows those only applicable in survey B. The middle column shows variable types applicable in both survey A and B. For full variable overview see appendix A.

First demographic variables were asked. Then a first (pre-treatment) redistributive scenario was presented. Respondents were informed about a mathematical task that the workers completed and which of the (anonymized) workers performed better. By default, the better performing worker was assigned the full bonus of $6, but was not informed yet of this. The respondents were asked how they would distribute the bonus over both workers. The distribution decision provides two variables: whether people redistributed some of the bonus to the lesser performing worker, and the amount that was redistributed. After the pre-treatment distributive choice, genetics was first mentioned and respondents were asked whether they had considered genetics in their distributive decision. Then respondents were asked for a heritability estimate as well as guess other respondents' average heritability estimate.

After this, treatment occurred. HighGen respondents were presented with information that the percentage in which differences in mathematical ability are explained by genetics (heritability) is 90%. The LowGen group was presented with a percentage of 20%. These estimates are the borders of the interval given by Docherty et al. (2010). There was no difference in questions asked between the treatment groups besides the information that was presented. Respondents were asked whether they were surprised by the provided information. Then they were tasked to make a second (post-treatment) redistributive choice, in the same way as the pre-treatment redistributive choice, again giving the variables of whether to redistribute and the amount that they redistributed.

Furthermore, respondents were asked qualitative questions. They were asked why they chose (not) to redistribute the bonus. Then followed a categorical question on whether they had considered genetics, with an accompanied qualitative question on why they thought the information to (not) be relevant. Based on the qualitative answers people could be categorized into 7 categories: Egalitarians, Performance Meritocrats, Genetic-Compensating Meritocrats, Genetics Minimizers, Information Lacking, Information Distrusting and Non-Classified. See appendix D for all definitions and further notes on categorization into types. Supplementary outcome variables were collected to confirm the effect of the treatment. These will not be the focus of this paper, but their scale and analysis can be found in appendices A and C.

Analysis methods

The analysis of dataset A is as follows. To observe the data, a balance table will be made of all outcome variables that are determined prior to treatment. This will be used to confirm successful randomization between treatment groups with a t-test with linear regressions for continuous variables and a Pearson's chi-squared test for categorical variables. It will additionally give a baseline for the distributive as well as respondents' estimates on the role of genetics and others' answers. The redistribution choices will be analyzed in multiple ways. Firstly, through two regressions, the effect of treatment is studied. Regression (1) studies the effect on whether someone redistributed, regression (2) the effect of the amount that someone redistributed. The regression equations are:

$$Redistributed2_i = \alpha_0 + \alpha_1 HighGen_i + \varepsilon_i \quad (1)$$

$$AmountRedistributed2_i = \beta_0 + \beta_1 HighGen_i + \theta_i \quad (2)$$

With HighGen being a binary variable for treatment depicting whether the individual i was in the HighGen group. This shows the effect of treatment on redistributive choices. The choice to redistribute and how much will additionally be presented graphically. Regression (2) will also be executed only including respondents who redistributed something.

People were categorized into personality types based on their reasoning behind their redistributive preferences. The qualitative answers of people on why they did (not) redistribute and why they thought the provided information on the role of genetics was relevant showed their thought processes and preferences. It is analyzed using a Pearson's chi-squared test as well as graphically whether the distribution of the categories is independent of treatment.

Treatment is intended to affect beliefs of people on the role of genetics. Thus, the variable Impact genetics which measures the perceived impact of genetics on the task performance should be affected by treatment. This variable will be used in a two-stage-least-squares regression, where treatment is the instrumental variable and impact genetics the variable of interest. Treatment is randomly assigned and affects the distributive choices only by altering beliefs about the impact of genetics, the independence assumption holds. Furthermore the treatment has no direct effect on distributive choices so the exclusion restriction holds. As long as the first stage is strong, all assumptions necessary hold for a valid estimation using an instrumental variable in a two-stage-least-squares regression measuring the causal effect that beliefs on the impact of genetics have on distributive choices (Lousdal, 2018).

Supplementary variables will also be compared between treatment groups, with linear regressions for continuous variables and Pearson's chi-squared tests for categorical variables. This will provide support for the validity of treatment as it includes questions on the impact of genetics as well as effort in the task of the workers and control workers had in the task.

3.2 Methodology B

Dataset B will be used to measure an extension to the topic of dataset A. Specifically it is used to study whether people make different redistributive choices simply as the result of mentioning genetics a possible factor determining performance. Furthermore, their reasoning for their distributive choices and other views will be tested. Survey B has a similar structure as survey A from Pogliano (2024). The survey flows are in large part similar, for comparison see figure 1. The survey is adjusted to correspond to the research aim of analysis B and to make it suitable for distribution in the Netherlands. The full survey can be found in Appendix E. Survey B was distributed between May 20th to June 1st. It was distributed through my personal network, using social media and flyers. A total of 157 people completed the survey. Out of those people, 15 failed the attention check (9.6% of total respondents), without any noticeable differences between treatment groups. These people were excluded in the analysis. There is no indication that this biases the research. Respondents were divided over three treatment groups with 49 respondents appointed to Control, 46 to Factors and 47 to Genetics.

Treatment survey B

The main difference between survey B and survey A is the treatment and introduction of the distributive task. Respondents only make one distributive choice in survey B instead of two. The introduction and choice for Control is similar to the pre-treatment distributive choice in survey A, although phrased as a hypothetical situation. The other two treatment groups will be presented with additional information. The information provided to Factors is: "Mathematical ability is the result of a

variety of factors." and the information provided to Genetics is: "Mathematical ability is the result of a **variety of factors**, one of which is **genetics.**" This information is presented twice: once at the introduction of the task and once right before the distributional choice. The selected bold words are also bold in the survey. This presentation makes it salient to respondents, ensuring that they read it twice. The information is only presented, no further questions are asked on it, to simulate a more realistic case of being presented with information as in a real-life situation. This also aims to minimize demand effects where respondents answer in a way is wanted by the researchers (Haaland et al., 2023; Pogliano, 2024). The presentation ensures that respondents read it, and limits the risk of steering respondents towards a 'preferable' answer. The treatment groups do not differ in any other way than the presented information.

Factors shows respondents that mathematical abilities are the result of a multi-factor model, in line with the research of Gericke et al. (2017). This might make respondents think more extensively about their redistributive choice. There is no clear hypothesis in what way this might change distributive choices as it could also lead respondents to focus more on either effort or merit. Genetics also mentions the multi-variable model that determines outcome, but highlights genetics. This treatment group is expected to assign higher importance of genetics, and make a more deliberate decision. This group is expected to redistribute more often and redistribute a higher amount to compensate for perceived luck. Genetics is the main treatment group of interest. Due to the similarities in wording with treatment Factors, the effects that could arise because people might make decisions more deliberately are separately analyzed. As such, it will be possible to separate the effects of stimulating people to make more careful decisions and the effects of additionally mentioning genetics. This minimizes bias that might occur if both possible effects were combined into one treatment group without comparable control group. For the validity of this research, an important assumption is that it is generally known that genetics have at least some influence on mathematical ability. That is why a question measuring this is added in survey B.

The pre-treatment distributional choice from survey A is similar to the distributional choice of the control group in survey B. The two distributional choices as used in survey A are suitable for within-subject analysis, although the interpretation is limited in that every respondent was exposed to some treatment (no control group). Furthermore, the first distributional choice might behave like an anchor, to which the second choice is adjusted (Chapman & Johnson, 1994). The set-up of survey B uses between-subject analysis that excludes this bias by randomizing treatment over respondents, while including a control group. Furthermore, survey B does not impose any assumptions on heritability. This solves the potential issue that respondents do not believe the information provided, which is present in survey A.

Outcome variables and analysis

The outcome variables of survey B are similar to those of survey A. However, the interpretation will differ due to the different types of treatment between the surveys. The main difference is that in survey B, there is only one distributive choice made. Moreover, there are slight changes in question order, some questions are dropped or added and there are some differences in categories for some categorical variables. This is done to be more suitable for distribution in The Netherlands. A specific change is that currency is expressed in euros. See appendix E for the complete survey B and appendix A for the variable overview. The categories in which people are classified based on their qualitative responses is somewhat different in survey B from survey A. This is due to the fact that the Control group and Factors group have no specific mention of genetics. The secondary data category of genetics-compensating meritocrat will be extended to include other circumstances mentioned (like home environment growing up) and will form a new category: circumstances-compensating meritocrat. As in the secondary data, someone compensating the loser for just effort, despite distributing most to the winner, without any mention of a (potential) difference in circumstances, whether genetics or otherwise, will be classified as a performance meritocrat. See appendix D for full information on categorization into types.

Analysis B is performed similarly to analysis A. It consists of the same variable (types) suitable for the same analysis methods. Only the two-stage-least-square regression is no longer suitable as the necessary assumptions do not hold and there is no other suitable instrumental variable.

Combined methodology

Finally, pre-treatment answers of survey A will be analyzed in combination with the distributional choices of the Control group of survey B. This might show differences between nationalities/cultures. This interpretation should be approached cautious due to selection bias in the distribution of survey B. Despite the fact that the post-treatment variables are mostly similar in the two surveys, they cannot be compared, since all respondents from survey A were presented with additional information on heritability and thus the answers are biased.

4 Results

4.1 Results A

Randomization and pre-treatment distribution

Before the application of treatment, the demographics and pre-treatment variables can be used to establish good randomization. As can be seen in table 1 and table C1, all pre-treatment variables used, are not statistically significant. This shows no indication of unsuccessful randomization and as such randomization assumed.

Table 1 Pre-treatment statistics dataset A

	Treatment group			
	LowGen	HighGen	Total	Test
N	241 (50.7%)	234 (49.3%)	475 (100.0%)	
Redistributed 1	0.643 (0.480)	0.641 (0.481)	0.642 (0.480)	0.962
Amount redistributed 1	1.182 (1.113)	1.184 (1.059)	1.183 (1.085)	0.982
Considered genetics 1	0.087 (0.283)	0.073 (0.260)	0.080 (0.272)	0.562
Heritability estimate	32.378 (22.515)	30.470 (22.558)	31.438 (22.533)	0.357
Others' heritability estimate	43.183 (20.432)	40.491 (20.340)	41.857 (20.410)	0.151

This table shows statistics for distributive pre-treatment variables for dataset A. There are four columns: LowGen separate, HighGen separate, a totals row and the p-value of the test for differences between the two treatment groups. Linear regressions are used to obtain the p-value. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). Redistributed 1 and Considered genetics 1 are binary numerical variables. For Redistribute 1 does 1 represent someone who redistributed and 0 represents someone who did not redistribute. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Without significant differences found, outcomes will be presented at the total group level. 64.2% (305 out of 475) of people redistributed some money to the person who did worse at the mathematical task. The average amount redistributed is $1.18, and the average amount redistributed given that someone redistributed is $1.84. As shown in figure B1, most people who redistributed, did so with either $1 or $2, with 11.4% of the sample (54 respondents) redistributed the bonus completely equally to both workers.

Additionally from table 1, we find that only 8% of people said that they considered genetics in their choice of how to redistribute. People furthermore estimate heritability lower than they expect others to do, with their own estimates averaging 31.4% and their estimates of the group average estimated heritability averaging 41.9%. This gap could be an indication of people feeling that the role of genetics is generally overestimated. In part, this can be explained by people misinterpreting the concept of heritability. Indications for this come from open-text answers as well as from critical literature such as Wray and Visscher (2008).

Post-treatment results of distributional choices

After treatment, respondents redistributed 71.8% of the time, compared before treatment where only 64.2% redistributed. In both treatment groups the percentage of respondents who redistributed increased, to 69.7% in the LowGen and 73.9% in the HighGen group. This could be due to the mention of genetics and heritability estimate, or because people rethought their initial distributional choice. The average amount redistributed also increased between the two distributional choices from $1.18 to $1.31 in the LowGen group and to $1.54 in the HighGen group (total post-treatment average being $1.42). For the full post-treatment outcomes, see table C5. Based on the regression results from table 2 there are no significant differences found between the two treatment groups in whether they redistribute. The difference with the first distribution could thus be due to just mentioning genetics in any way and letting respondents rethink their distributional choice. There are significant differences however in the amount they redistribute and the amount they redistribute given that they redistribute. This indicates that in situations where genetics play a large(r) role in performance, a higher level of redistribution is desired.

Table 2 Regression results dataset A

	Redistributed 2	Amount redistributed 2	Amount redistributed 2 given redistributed 2
HighGen	0.0422	0.237^{*}	0.214^{*}
	(0.0413)	(0.102)	(0.0859)
Constant	0.697^{***}	1.306^{***}	1.874^{***}
	(0.0297)	(0.0726)	(0.0671)
Observations	475	475	341
Adjusted R^2	0.000	0.009	0.015

This table shows the regression results for three linear regressions with dataset A. Columns 2 and 3 have the same dependent variable, but for column 3 only respondents who redistributed were selected. Redistributed 2 is a binary variable where 0 represents a non-redistributing respondent, and 1 represents a respondent who did redistribute. Standard errors are depicted in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2 shows a histogram of the distributional choices between the two treatment groups. Besides the HighGen group redistributing more often, the differences in the amounts are also clearly visible. The HighGen treatment group redistributes $1 less often, while redistributing $2 and $3 more often. There is a noticeable different distribution of Amount redistributed 2 between treatment groups, and these differences are statistically significant.

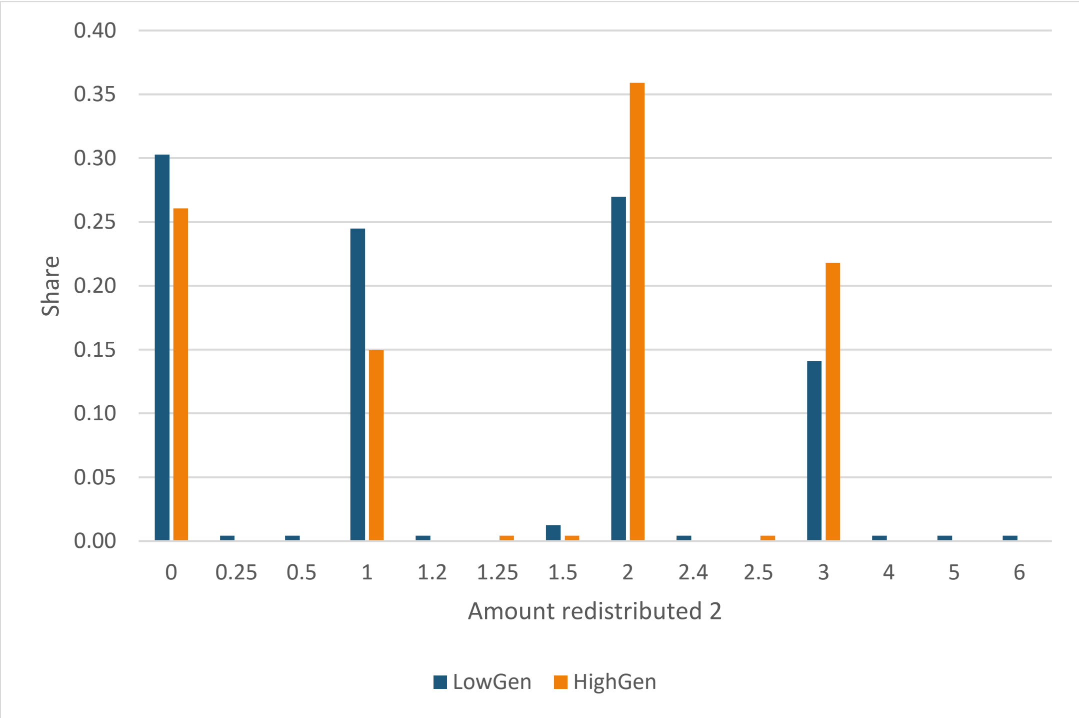

Figure 2 Distribution of Amount redistributed per treatment group, dataset A

The LowGen and HighGen groups differ significantly in whether they considered genetics in their second distribution. In the LowGen and HighGen respectively, only 3.7% and 0.4% of respondents reported to have forgotten completely about any role of genetics, whereas 34.4% and 49.1% of respondents found it relevant. This is an incredible increase in the fraction of people who considered genetics in the second distributional choice, compared to the first.

Each respondent was categorized as one of the following types: Egalitarian, Performance Meritocrat, Genetic-Compensating Meritocrat, Genetics Minimizer, Information Lacking, Information Distrusting and Non-Classified. Further specification and notes on the categories and categorization can be found in Appendix D. As shown in figure 3, the types differ significantly between the treatment groups (exact numbers can be found in table C5). The most notable differences are apparent for the categories genetics-compensating and genetics minimizer. The former has a much higher occurrence in the HighGen group, while the latter is much more prominent in the LowGen group. This is in accordance with expectations. Someone who feels that there could be reason to compensate a loser for a (likely) genetic disadvantage would more likely fall under genetics minimizer in the LowGen group. This same person would quicker fall under genetics-compensating when in the HighGen group. Genetics minimizer and genetics-compensating people are people who care about genetics. 36.6% of the total respondent group falls in either of those categories (37.3% in LowGen, 35.9% in HighGen). The more principle-based categories: performance meritocrat and egalitarian do not differ between groups. This indicates that these categories are correctly and validly assigned.

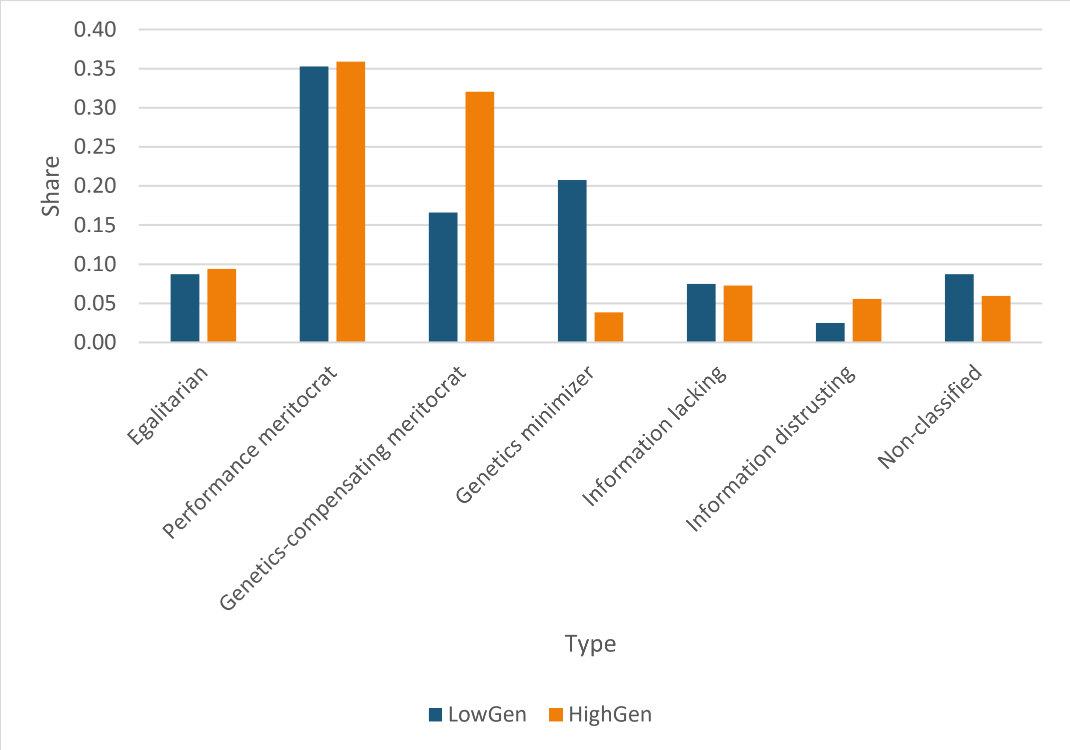

Figure 3 Distribution of Type per treatment group, dataset A

Analyzing individual choices for redistribution, we see that most people (71.6% of respondents) do not change their distributional decision after treatment. This percentage is much higher for the LowGen (76.8%) group than for the HighGen group (66.2%). Furthermore, given a change in redistribution, people in the HighGen group changed their redistribution more often by a larger amount. For exact data on changes in distributional choices, see tables C2 and C3.

Given that the treatment of informing respondents about heritability only alters peoples' beliefs on the impact that genetics has on performance in the mathematical task, an instrumental variable two-stage-least squared regression can look at the effect of an increase in impact of genetics on distributional preferences. The first stages of the two-stage-least-square regression all were significant and of a large enough size, as shown in table C4. Table 3 does not show significant differences of the perceived impact of genetics (on a scale of 0-10) on whether someone redistributed. There are, however, significant positive effects found of the judged impact of genetics on the amount redistributed. These effects are also found in the case where only respondents who redistributed were taken into account. People in these cases redistributed respectively $0.07 and $0.06 more per point in which they judged genetics to affect performance. The pattern of significance is the same as in the simple regressions of treatment on these outcome variables. This seems to indicate that inequalities caused by genetics are deemed undesirable and give reason for (higher) redistribution. The found differences are in line with the expectation and are explained by treatment having affected beliefs on the impact of genetics, and those beliefs lead to a preference for higher redistribution.

Table 3 IV regressions with treatment (HighGen) as the instrumental variable dataset A

	Redistributed 2	Amount redistributed 2	Amount redistributed 2 given redistributed 2
Impact genetics	0.0124	0.0698*	0.0607*
	(0.0120)	(0.0294)	(0.0240)
Constant	0.662***	1.110***	1.692***
	(0.0578)	(0.141)	(0.123)
Observations	475	475	341
Adjusted R^2	0.018	0.047	0.034

This table shows the regression results for three two-stage-least-squares regressions with dataset A. The instrumental variable is treatment (HighGen). Columns 2 and 3 have the same dependent variable, but for column 3 only respondents who redistributed were selected. Redistributed 2 is a binary variable where 0 represents a non-redistributing respondent, and 1 represents a respondent who did redistribute. Standard errors are depicted in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Other post-treatment variables and validity of treatment

Almost all other post-treatment variables differ significantly between treatment groups, as can be seen in table C5. The signs of the differences are in line with the expectations. The manipulation questions show successfully affected beliefs. The estimates of heritabilities for other factors show differences that could be in line with anchoring and adjustment corresponding to a differing level of a 'normal' heritability (Chapman & Johnson, 1994). The mechanism variables give an indication of genetics being viewed as luck for which is regarded as being less fair, as theorized based on Cappelen et al. (2017) and Almås et al. (2020). The successful manipulation of the treatment shows support for the validity of the treatment, and with that the validity of the research. This can also be seen from correlations in table C6. However, there seems to be some distrust about the provided heritability estimate, especially in the HighGen group, based on the 'Surprised' and 'Accuracy study' variables. As the provided heritabilities were borders of the given interval by Docherty et al. (2010), some surprise is to be expected, but the differences between groups could be an indication of some limitation. It is likely for a large part due to the (incorrect) causal interpretation of the heritability concept (Wray & Visscher, 2008). This will be further discussed in the Discussion and is the reason for different treatments used in survey B.

4.2 Results B

Randomization and demographics

Respondents in survey B were randomly assigned to three groups: Control, Factors or Genetics. table C7 shows the demographics of the respondents of survey B. No variables with a significant difference in distribution between groups are found. Randomization is assumed since there is no reason to suspect unsuccessful randomization. However, the demographical statistics indicate deviation of the sample from the whole population. From this it can be derived that distribution of survey B occurred biasedly and is not representative of the whole population.

Distributional choices

The only significant differences in distributional decision-making is found for the variable Considered genetics, as shown in tables 4 and C8. This indicates that the treatment had some effect on the thought process of respondents in their distributional task. As expected, the Control group considered genetics less than the Factors group, who in turn considered it less often than the Genetics group. Interestingly, of those who considered genetics, people in the Control group report that it affected their distribution the most (12 out of 17), then follows the Genetics group (13 out of 29) and finally the Factors group (8 out of 21). This gives an indication that the Factors group made people consider the various factors that could affect mathematical ability, but that genetics was less often a deciding factor for their distributive choice. The control group might not consider genetics often, but people who did, were likely to let this affect their distribution, while the control group more often did not change their distribution as a result of it. These results can also (partly) explain why no significant differences in whether to distribute and by how much are found. The distribution of types is not significantly different across treatment groups, however, the only people who in their open text answers mentioned compensating for genetics specifically were in the Genetics group. This matches the above discussed results. Figures B2 and B3 show the similarities in distribution per treatment group over the Amount redistributed and Type respectively.

Table 4 Distributional choices and considered genetics dataset B

	Treatment group				
	Control	Factors	Genetics	Total	Test
N	49 (34.5%)	46 (32.4%)	47 (33.1%)	142 (100.0%)	
Redistributed	0.633 (0.487)	0.717 (0.455)	0.723 (0.452)	0.690 (0.464)	0.565
Amount redistributed	1.347 (1.128)	1.630 (1.185)	1.638 (1.164)	1.535 (1.159)	0.375
Considered genetics					
No, I did not think about it	32 (65.3%)	25 (54.3%)	18 (38.3%)	75 (52.8%)	0.031*
Yes, but it did not change anything about my distribution	5 (10.2%)	13 (28.3%)	16 (34.0%)	34 (23.9%)	
Yes, and it affected my distribution	12 (24.5%)	8 (17.4%)	13 (27.7%)	33 (23.2%)	

This table shows statistics for distributive variables and whether someone considered genetics, including explanation for dataset B. There are five columns: Control, Factors, Genetics, a totals row and the p-value of the test for differences between the three treatment groups. For numerical variables linear regressions are used to obtain the p-value, for categorical variables this is a Person Chi-squared test. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). Redistributed is a binary numerical variables where 1 represents someone who redistributed and 0 represents someone who did not redistribute. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The estimated heritability of all respondents was 46.5%. There was a general consensus that genetics play a role in mathematical ability, but do not fully decide mathematical ability (4.2% saying otherwise). This, and the fact that no differences in distribution of beliefs between groups are found, support the assumption that generally some role for genetics is accepted, in combination with other factors, in forming mathematical ability.

Table 5 shows no significant effect of treatment on any of the shown distributive choices. This is also the case when only two of the treatment groups are included in the regression on amount redistributed, as table C9 shows.

Table 5 Regression results dataset B

	Redistributed	Amount redistributed	Amount redistributed given redistributed
Factors	0.0847	0.283	0.144
	(0.0967)	(0.238)	(0.156)
Genetics	0.0908	0.291	0.136
	(0.0959)	(0.234)	(0.151)
Constant	0.633***	1.347***	2.129***
	(0.0696)	(0.161)	(0.101)
Observations	142	142	98
Adjusted R^2	-0.006	-0.000	-0.010

This table shows the regression results for three linear regressions with dataset B. Columns 2 and 3 have the same dependent variable, but for column 3 only respondents who redistributed were selected. Independent variables Factors and Genetics are dummy variables for treatment, with the Control group included in the constant. Redistributed is a binary variable where 0 represents a non-redistributing respondent, and 1 represents a respondent who did redistribute. Standard errors are depicted in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.3 Combined results

It is possible to compare the control group of the primary data collection with pre-treatment variables in the secondary data collection to analyze differences between samples, and with that possibly cultures/nationalities. Demographics can be found in table C10, which shows significant differences between respondent groups. These differences can be mostly explained by ways of survey distribution. Interestingly, the groups also differed in their heritability estimates and whether they considered genetics without it having been mentioned at that point, see table 6. This could be a cultural difference, although this cannot be surely concluded due to biased distribution and possible differences in interpretation.

Table 6 statistics non-demographic variables combined samples

	Sample			
	Sample A	Sample B	Total	Test
N	475 (90.6%)	49 (9.4%)	524 (100.0%)	
Redistributed (1)	0.642 (0.480)	0.633 (0.487)	0.641 (0.480)	0.896
Amount redistributed (1)	1.183 (1.085)	1.347 (1.128)	1.198 (1.089)	0.315
Heritability estimate	31.438 (22.533)	47.490 (20.275)	32.939 (22.799)	<0.001***
Considered genetics (1)	0.080 (0.272)	0.347 (0.481)	0.105 (0.307)	<0.001***

This table shows statistics for distributive variables, heritability estimate and whether someone considered genetics. The columns are split into four: sample A separate, sample B (only control group) separate, a totals row and the p-value of the test for differences between the two groups. Linear regressions are used to obtain the p-value. The (1) represents that these variables were measured twice for sample B and once for Sample A, see table A1. Amount redistributed (1) has different currencies between samples, with USD for sample A and EUR for sample B, the amount should be interpreted relative to the total of 6 USD/EUR. Sample B only includes those from sample B assigned to the Control group. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). Considered genetics (1) is a binary numerical variable where 1 represents 'yes' and 0 represents 'no'. Redistributed (1) is a binary numerical variables where 1 represents someone who redistributed and 0 represents someone who did not redistribute. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The samples differ in demographics, their base level heritability estimates and whether they considered genetics. Despite these differences, there are no found significant differences in the main redistributive choices, as depicted in table 7. However, there are significant differences found in the amount that is redistributed, given that someone redistributes. This shows that in sample A (only Control group) people redistributed more than in sample B, given that they distributed. Respondents in sample B opted more often to redistribute 2 rather than 1 euro, while those in sample A opted more often to redistribute 1 dollar rather than 2 dollar, as can be seen in figure 4. This could be an indication of cultural differences between the USA and the Netherlands.

Table 7 Regression results combined datasets

	Redistributed	Amount redistributed	Amount redistributed given redistributed
Dataset B	-0.00945	0.164	0.287**
	(0.0724)	(0.167)	(0.109)
Constant	0.642***	1.183***	1.842***
	(0.0220)	(0.0498)	(0.0451)
Observations	524	524	336
Adjusted R^2	-0.002	0.000	0.009

This table shows the regression results for three linear regressions with combined samples. Columns 2 and 3 have the same dependent variable, but for column 3 only respondents who redistributed were selected. Amount redistributed (1) has different currencies between samples, with USD for sample A and EUR for sample B, the amount should be interpreted relative to the total of 6 USD/EUR. Redistributed 2 is a binary variable where 0 represents a non-redistributing respondent, and 1 represents a respondent who did redistribute. Dataset B is 1 when a respondent answered survey B, otherwise the value is 0 for respondents who answered survey A. Standard errors are depicted in parentheses. *$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

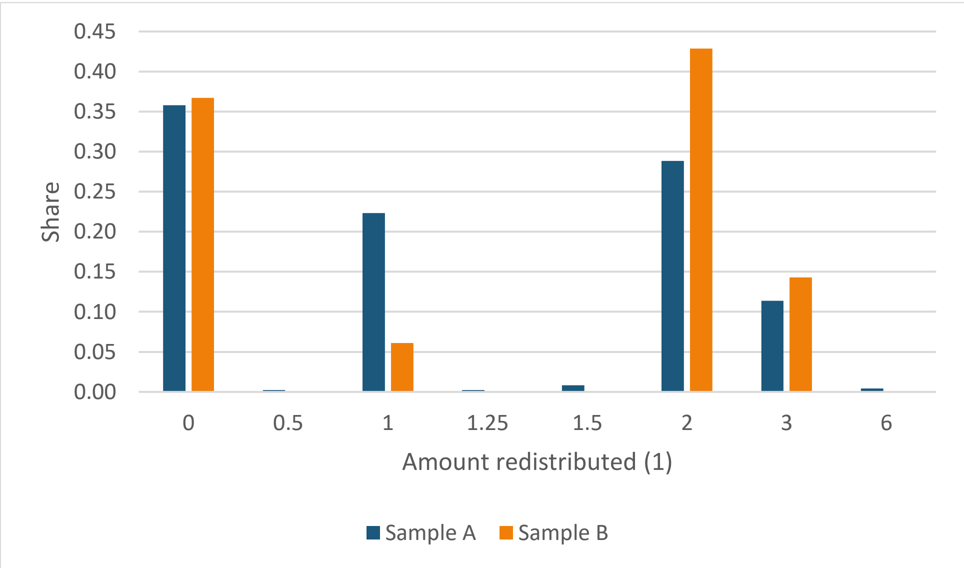

Figure 4 Distribution of Amount redistributed (1) per sample group, combined datasets

5 Discussion

This paper looked at inequality and redistribution, specifically analyzing the effects of performance influenced in various amounts by genetics on peoples' beliefs and preferences. This was done as an expansion of the existing theories that people generally prefer a meritocratic distribution, in which rewards are based on effort and performance (Cappelen et al., 2013; Kim & Choi, 2017; Grant, 2018). People perceive situations as being more fair when they are determined by effort rather than luck (Cappelen et al., 2013; Cappelen et al., 2017; Almås et al., 2020). Since genetics are given by one's parents, they can be categorized under luck (Coop & Przeworski, 2022; Harden, 2021; Harden 2022). This paper performed studied this topic through in multiple ways. Firstly, by using secondary dataset A it was assessed whether the size of the role of genetics matters for peoples redistributive preferences and further beliefs. Secondly, it was assessed using primary dataset B whether mentioning genetics affected peoples' beliefs and preferences. Thirdly and finally, the datasets A and B were compared to research potential differences between respondent groups with different nationalities and cultures, inspired by Almås et al. (2020).

Analysis A

Analysis A used data from Pogliano (2024) who based his survey and treatment on Haaland et al. (2023). There were two treatment groups, they were either told that genetics played a large or small role in genetics (heritabilities of respectively 90% and 20% were provided). Randomization was successful, leaving the results to be causally interpretable. Without treatment, the respondents redistributed on average 64.2% of the time with an average amount redistributed of $1.18. Initially only 8% of people considered genetics without it having been mentioned. After treatment, both the LowGen and HighGen groups redistributed more often and with a higher average amount compared to pre-treatment, and the average amount given that someone redistributed also increased. No significant effects of treatment on how often people redistribute were found, but significant effects were found on the amount redistributed and the amount redistributed given that someone redistributed. The difference with the first distribution can in part be a result of mentioning genetics and/or have respondents rethink their distributional choice. The significant findings indicate that in situations in which genetics play a large(r) role in outcomes, a higher level of redistribution is desired. The same pattern of significance is found in a two-stage-least square regression where treatment is the instrumental variable for the intermediary variable Impact genetics. These regression results match the expectation and form an indication that treatment successfully affects beliefs. Remarkably, most people did not change their distribution after treatment (71.6%), especially in the LowGen group. Although estimated heritabilities (31.4%) were closer to the LowGen provided heritability, this does not really explain this difference, since most people did not consider genetics in their first distributive choice.

I furthermore categorized respondents into types of people based on their reasoning about why they redistributed and the role that genetics played in their choice. This confirmed the hypothesis that people are more inclined to prefer redistribution when genetics play a larger role in performance. The types based more on fundamental principles (e.g. performance meritocrat and egalitarian) had similar densities between treatment groups. Other relevant categories: genetics-compensating and genetics minimizer, differed between groups, with respondents in the HighGen group more often being the former type and respondents in the LowGen group the latter type. This supports the general finding of people preferring more redistribution when genetics plays a large role in performance.

It can be concluded that treatment had significant effect on peoples beliefs, supporting the validity of the treatment. This is found by significant differences between treatment groups in manipulation questions, other estimated heritabilities and mechanisms. There are however also some limitations to this study.

Firstly, a limitation is about interpretation of the results. Survey A had two treatment groups, and no control group, the results should be interpreted with this in mind. The results per treatment group can only be interpreted relative to the other group. Interpretation is only about the sign of effects, the exact effect size has no (directly applicable) interpretation. This is especially the case since the two treatment groups were provided with either an extremely high or low estimate for heritability (Docherty et al., 2010). Thus, the found results are only measurements of the differences between extreme estimated heritability, in a binary, non-continuous manner. Supplementary post-treatment variables can also only be interpreted as a group average rather than a population average.

Secondly, valid research in needs the treatment to successfully manipulate beliefs. While it did change beliefs on the role of genetics in accordance with expectations, there are indications of this not being fully successful. People reported distrust about the accuracy of the study and many respondents were surprised by the given heritability estimate. Disbelief was also found in the analysis of qualitative answers. This disbelief is especially noticeable for the HighGen group. A likely cause for this is that people misinterpret the heritability concept to be causal (Visscher et al., 2008). Such incorrect interpretation might affect answers in redistributive choices. Since the treatment still affected beliefs, just not fully, this is not that much of a concern, especially with the relative interpretation of results between treatment groups.

Analysis B

Survey B is designed and used to study the effect of mentioning genetics on distributive choices. Based on literature, the expectation was that this would increase redistribution as the availability heuristic can lead to a larger perceived role of genetics (Spiers, 2002; Esgate & Groome, 2005; Tversky & Kahneman, 1973). Survey B tried to solve some of the limitations of analysis A by including a control group and not having extremes as treatment. Randomization successfully occurred over three groups: Control, Factors and Genetics. Treatment seems to have had the intended effect of making more people consider a possible role of genetics (as well as other factors). However, no significant differences in distributive choices nor categorization in types of people were found. A general limitation of analysis B is the small, non-representative sample. This is a limitation to the external validity.

Furthermore, analysis B has the implementation and saliency of the treatment as the main limitation to the internal validity. While the treatment sentence was included twice with relevant words bold-faced, some respondents might still have missed it or quickly skipped over it without internalizing the information. The treatment had some effect, but the effect could have been too small to cause significant changes in beliefs and distributive choices. The saliency of the treatment was attempted to be well balanced with ensuring the validity without differences in manipulation. After all, this could have introduced other effects such as demand effects, where respondents might base their choices on what they thought was expected of them (Haaland et al., 2023; Pogliano, 2024). Treatment was implemented to avoid these effects, but it might have limited the saliency of treatment, which might explain the lack of found significant effects. Based on the increase in redistribution in the second distributional choice compared to the first in analysis A, this seems a possible explanation. It is however merely speculative as there was no control group in survey A and the found difference could also be due to demand effects (Haaland et al., 2023; Pogliano, 2024). Another limitation is that the Genetics group, to avoid unequal manipulation methods, was also told that mathematical ability is the result of a variety of factors. This could have distracted the focus from just genetics to also other factors.

Combined analysis

Datasets A and B can be compared to research differences in distributive preferences between respondent groups and as such nationalities/cultures. For this, variables had to be similar and not affected by any treatment, so only selected variables (pre-treatment variables for survey A) and selected respondents (Control for survey B) were used for this analysis. Despite large, significant changes in groups, their baseline estimates of heritability and in whether they considered genetics, no significant differences in distributive choices were found for whether to redistribute and the amount that was redistributed. However, there were significant results found in that the primarily Dutch survey

B respondent group redistributed more than US based respondent group from survey A did, given that they redistributed. This could be linked to a more egalitarian approach in the Netherlands, but due to bias caused by treatment this cannot be confirmed with the data that is collected.

The combined results should be interpreted extremely careful as there are multiple limitations that could introduce bias. The main limitation is the method of distribution of the surveys. Survey A was distributed within the USA, while survey B was distributed through my personal network, primarily in the Netherlands. Both samples, especially sample B are not representative of the general population. Furthermore, some things changed between surveys. This includes changing currencies, different answer categories and the framing of the distributive choice as being hypothetical in survey B. Finally, answers to questions can be interpreted differently between respondent groups due to language barriers or differing interpretations due to cultural differences. For example, a political stance from left to right by a Dutch person has a different meaning in terms of policy preferences than asking a US-citizen which political party best reflects their opinions. Considering this all, the combined analysis is very limited in their interpretation.

Further research and policy implications

This research gives multiple options where further research can be useful and is recommended. The results from analysis A can be expanded to include a more continuous scope of given heritabilities, rather than just the extremes of 20% and 90%. This would provide information on differences in redistributive preferences. Furthermore, a control group can be a good way to obtain a population-wide average for post-treatment variables. Additionally, a clear distinction between providing a heritability estimate and a causal interpretation could be studied. Combine this with a good clear presentation to respondents. With these additions, the results will be directly interpretable rather than just relatively. The set-up in case has low stakes, with a bonus of $6 (or €6), without large implications for real-life. Including higher stakes complements the research of Andre (2021) showing that decisions on inequality might differ in real-life examples rather than an experimental small scale set-up. Repeating this in different cultural contexts would be interesting as it can show cultural differences, since cultural context is important for forming people's beliefs and preferences (Almås et al., 2020). Here, it is important to ensure that the values are comparable, not (differently) affected by treatment. Other factors could also be introduced, like situations in which research subjects are stakeholders or simply observants, similar to what Capellen et al., (2013) researched for situations on general luck. This could be expanded with a role for genetics.

Analysis B could be repeated with a more salient treatment, and with different wordings for the treatment groups to provide a proper overview. More respondents and a more representative sample would be required for this. Research aimed at separating different factors affecting performance, and beliefs regarding those should be done as the focus on genetics should not overrule other factors playing important roles. As heritability is a fluid concept, losing focus on other factors (e.g. upbringing, schooling) could provide a feedback loop of more and more focus of genetics (Wray & Visscher, 2008).

Finally, further research could be done in the political-philosophical fields regarding applications of found redistributive preferences regarding genetics and societal consequences this could have. As Harden (2021) wrote, genetics-compensating policies could prove to have enormous positive consequences, however this should be approached with care (Coop & Przeworski, 2022; Harden, 2022) as it could misused by politicians.

From this research, it was found that people's beliefs on the role of genetics influence their redistributive preferences. When genetics was shown to play a large role in performance, people thought it fair to redistribute more than when genetics had a small role. This shows that some people care about genetics. However, a lot of people prefer a more egalitarian or meritocratic approach, possibly including a special reward for effort. The balance between these views should be kept in mind by policymakers in order to honor everyone's preferences. In total there seems to be evidence that inequalities arising due to genetics might be regarded as unfair and people should be compensated for this. The role of genetics and the importance of it is extremely relevant for policy decisions. When genetics is perceived to play a small role, this role is often minimized. Then people think there is less of a need for redistribution, while a large role for genetics can be cause for more redistribution. The interaction between environmental factors and how they can influence the inequality stemming from genetics as discussed by Arold et al. (2024) could also have serious implications for policies aiming not at compensating for, but rather at reducing inequalities stemming from genetics. Schooling and ensuring equality of opportunity can reduce inequalities stemming from genetics. Investing in this could lower the need for redistributive policies since the inequality levels will be lower. The problem of inequality is then solved at the root. Policy-makers could use the views on inequality, redistribution and genetics as discussed in this paper for policies that have a preventative and/or redistributive aim, and implement such policies in fields where it is known that genetics play a significant role.

6 Conclusion

This paper studied the question: *"What do people think about redistribution in a meritocratic situation and how do their beliefs and preferences change when the role of genetics is either large or small, and what is the effect of mentioning genetics?"* This was done using two surveys with an experimental set-up. Both experiments asked respondents to make one or two distributional choices after being presented with information about performance in a mathematical task, along with several other questions measuring beliefs and opinions. The first experiment measured the effect of telling people that genetics either played a small role or large role (heritabilities of respectively 20% and 90%). Here it was found that a larger role of genetics was reason for people to redistribute more on average, also when filtered on that people redistributed. No significant effect was found on whether people redistributed. The found reason for this is that in the 20% group, people often judged genetics to not play a main contributing role, whereas people in the 90% group did think genetics did have such a role. That gave reason for the latter group to redistribute more. The second experiment measured the effect of mentioning genetics, with three groups: a control group, a group presented with information that various factors contribute to performance, and a group presented with the additional information that one of those factors is genetics. While this did significantly affect whether people considered genetics in their distributive choice, no significant effect on distributional choices was found. While more research should be done, specifically on the topic of mentioning genetics, this paper increased understanding on beliefs and preferences on inequality, redistribution and fairness when genetics are at play.

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Appendices

Appendix A Variable overview

Appendix B Additional figures

Appendix C Additional tables

Appendix D Notes on categorization of types

Appendix E Survey B

Appendix A Variable overview

Table A1 overview of variables

Survey Part Origin	Variable Name	Scale type and scale	Notes
Demographics	Gender	Categorical	3,5
	Age	Numerical	5
	Education	Categorical	3,5
	Political stance	Categorical	3,5,6
	Income	Categorical	3,5,6
	Religious activity	Categorical	5
Distribution 1	Redistributed 1	Binary Yes/No	4,5
	Amount redistributed 1	Numerical 0-6	4,5
Role of genetics & Priors	Considered genetics 1	Binary Yes/No	3,4,5
	Heritability estimate	Numerical 0-100	5
	Other's heritability estimate	Numerical 0-100	1
	Beliefs role genetics	Categorical	2
Distribution 2	Surprised	Categorical	1
	Redistributed 2	Binary Yes/No	1
	Amount redistributed 2	Numerical 0-6	1
Open question(s)	Considered genetics 2	Categorical	1
	Type	Categorical[3]	3
Manipulation questions	Impact genetics	Numerical 0-10	
	Control	Numerical 0-10	
	Responsibility	Numerical 0-10	
	Fairness	Numerical 0-10	
	Impact effort	Numerical 0-10	
	Environment	Binary Yes/No	
External/Other heritabilities	Personality	Numerical 0-100	
	Mental health	Numerical 0-100	
	IQ	Numerical 0-100	
	BMI	Numerical 0-100	
MEC/Mechanisms	Success fairness	Numerical 0-10	
	Nature fairness	Numerical 0-10	
	Efficiency fairness	Numerical 0-10	
	Accuracy study	Numerical 0-10	1
	Policies	Numerical 0-10	2
Mathematical ability	Mathematical ability	Categorical	
Treatment	HighGen	Binary Yes/No	1
	Treatment	Categorical - Control/Factors/Genetics	2

In principle, all variables are used in both analysis A and analysis B, with some exceptions and differences between surveys or analysis, see notes below.

1) This variable is only used in survey A
2) This variable is only used in survey B

3) Categories that could be selected were adjusted between survey A and survey B due to the different area of distribution.
4) In survey B this variable occurs only once, so the number 1 after the variable is removed for analysis B
5) This variable is used for the combined analysis. Note that if in combination with 3, the different categories are combined for them to be comparable (with the exception of income).
6) In analysis, the original answer options of this variable might be recategorized for validity (mostly for validity of Pearson's chi-squared test).

Appendix B Additional figures

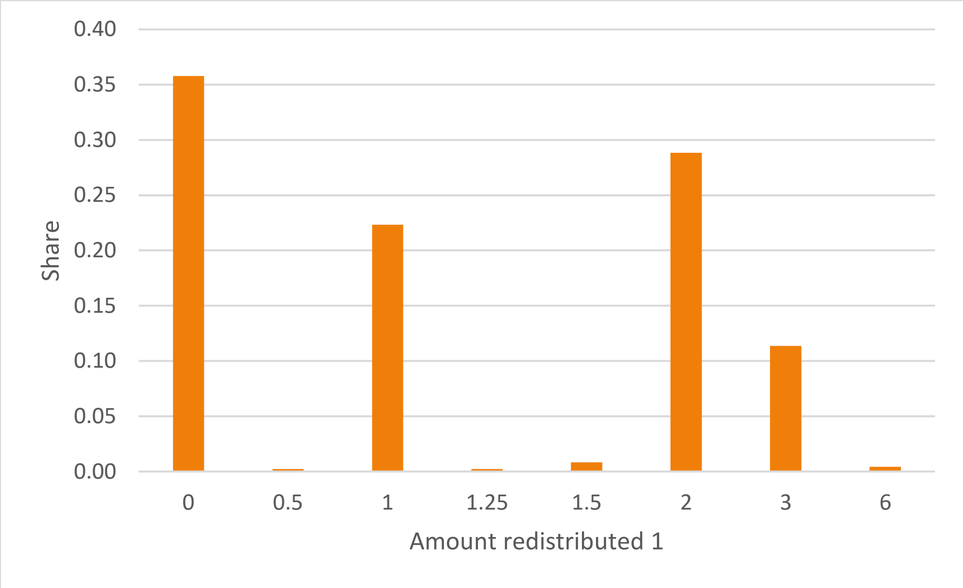


Figure B1 Distribution of Amount redistributed 1, dataset A

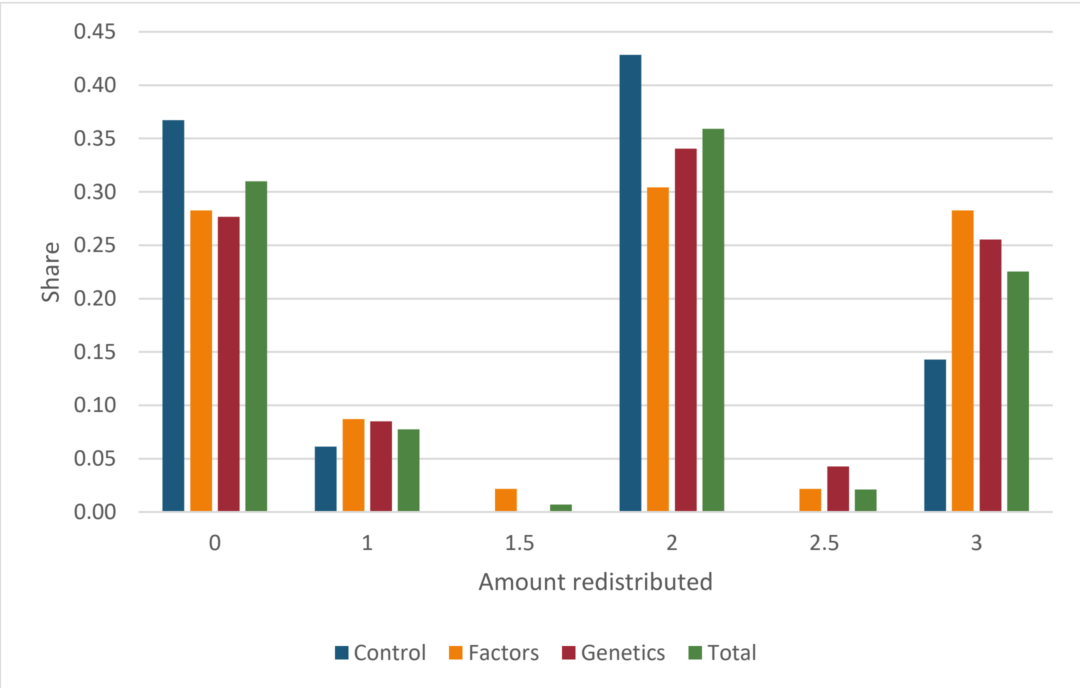


Figure B2 Distribution of Amount redistributed per treatment group and for the total sample, dataset B

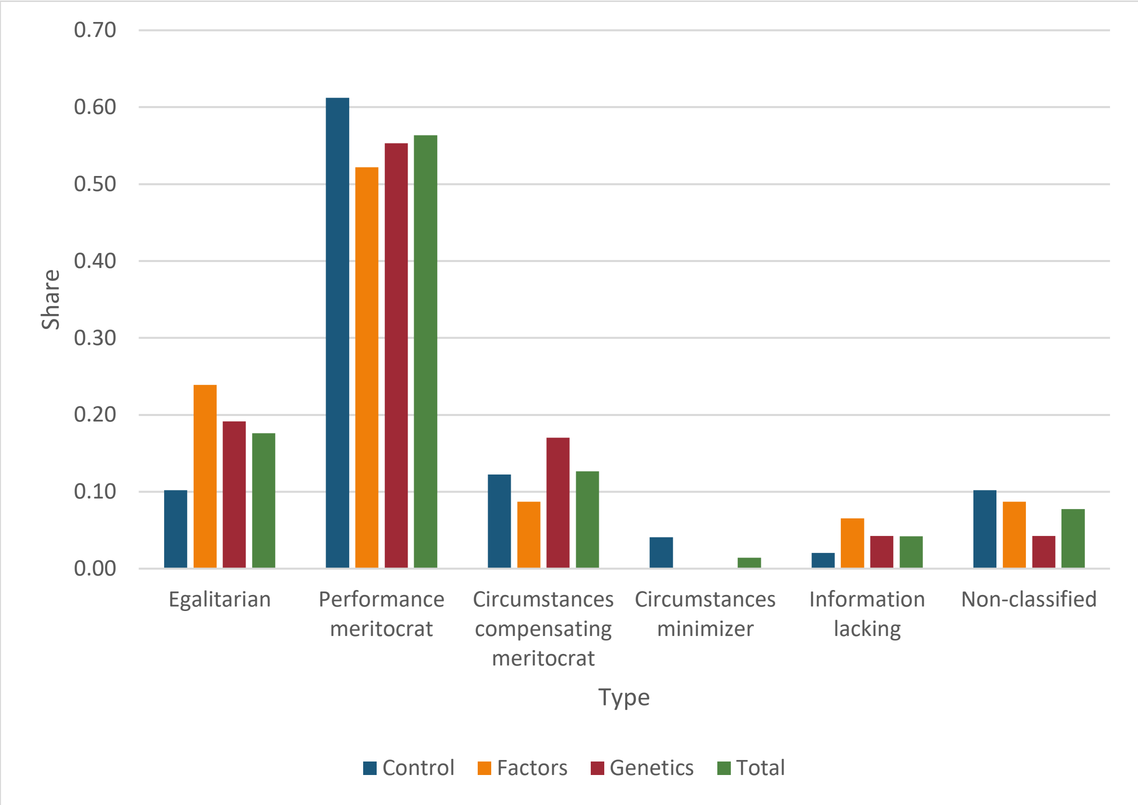


Figure B3 Distribution of Type per treatment group and for the total sample, dataset B

Appendix C Additional tables

Table C1 Demographics dataset A

	Treatment group			
	LowGen	HighGen	Total	Test
N	241 (50.7%)	234 (49.3%)	475 (100.0%)	
Gender				
Male	97 (40.2%)	81 (34.6%)	178 (37.5%)	0.263
Female	143 (59.3%)	153 (65.4%)	296 (62.3%)	
Other	1 (0.4%)	0 (0.0%)	1 (0.2%)	
Age	41.585 (14.423)	41.786 (14.208)	41.684 (14.303)	0.878
Education				
Less than High School	1 (0.4%)	0 (0.0%)	1 (0.2%)	0.759
High School	25 (10.4%)	25 (10.7%)	50 (10.5%)	
Some college	67 (27.8%)	73 (31.2%)	140 (29.5%)	
Bachelor's Degree	90 (37.3%)	86 (36.8%)	176 (37.1%)	
Master's Degree	42 (17.4%)	41 (17.5%)	83 (17.5%)	
Doctorate or Professional Degree	15 (6.2%)	8 (3.4%)	23 (4.8%)	
I prefer not to disclose	1 (0.4%)	1 (0.4%)	2 (0.4%)	
Political stance				
Democrat	124 (51.5%)	129 (55.1%)	253 (53.3%)	0.266
Republican	51 (21.2%)	36 (15.4%)	87 (18.3%)	
Independent	66 (27.4%)	69 (29.5%)	135 (28.4%)	
income in three categories				
$0 to $30,000	85 (36.3%)	85 (36.6%)	170 (36.5%)	0.488
$30,000 to $70,000	81 (34.6%)	90 (38.8%)	171 (36.7%)	
Over $70,000	68 (29.1%)	57 (24.6%)	125 (26.8%)	
Religious activity				
Never	102 (42.3%)	98 (41.9%)	200 (42.1%)	0.523
Rarely	56 (23.2%)	63 (26.9%)	119 (25.1%)	
Several times a month	23 (9.5%)	28 (12.0%)	51 (10.7%)	
Once a week	35 (14.5%)	22 (9.4%)	57 (12.0%)	
Multiple times a week	21 (8.7%)	18 (7.7%)	39 (8.2%)	
I prefer not to disclose	4 (1.7%)	5 (2.1%)	9 (1.9%)	

This table shows statistics for demographics for dataset A. There are four columns: LowGen separate, HighGen separate, a totals row and the p-value of the test for differences between the two treatment groups. For numerical variables linear regressions are used to obtain the p-value, for categorical variables this is a Person Chi-squared test. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). * p < 0.05, ** p < 0.01, *** p < 0.001.

Table C2 Overview of changes in distributional choices HighGen, dataset A

		Change in redistribution ((Amount redistributed 2) – (Amount Redistributed 1))										
		-3	-2	-1	-0.5	0	0.5	1	1.5	2	3	4	Total
Amount redistributed 1	0					57		6	1	14	6		84
	0.5								1				1
	1			1		26		17		5			49
	1.5					1	2						3
	2		2	2		47	1	16					68
	3	1	1	3		24							29
	6												0
	Total	1	3	6	0	155	3	39	2	19	6	0	234

This table shows the number of respondents per combination of amount redistributed 1 and the difference between distributional choices in dataset A for respondents in the HighGen group. Empty cells represent 0. Adding the amount redistributed 1 and change in redistribution together gives the amount redistributed 2. All amounts are rounded to the nearest 0.5, 1 respondent was affected by this.

Table C3 Overview of changes in distributional choices LowGen, dataset A

		Change in redistribution ((Amount redistributed 2) – (Amount Redistributed 1))										
		-3	-2	-1	-0.5	0	0.5	1	1.5	2	3	4	Total
Amount redistributed 1	0					67	1	7	1	7	3		86
	0.5												0
	1			2	1	43		7	1	2		1	57
	1.5					1				1			2
	2		1	9	1	51		6		1			69
	3	3				22							25
	6	1				1							2
	Total	4	1	11	2	185	1	21	2	11	2	1	241

This table shows the number of respondents per combination of amount redistributed 1 and the difference between distributional choices in dataset A for respondents in the LowGen group. Empty cells represent 0. Adding the amount redistributed 1 and change in redistribution together gives the amount redistributed 2. All amounts are rounded to the nearest 0.5, 5 respondents were affected by this.

Table C4 First stage regressions for IV-regressions dataset A

	impact genetics	impact genetics given redistributed 2
HighGen	3.401***	3.526***
	(0.223)	(0.244)
Constant	2.817***	3.006***
	(0.145)	(0.167)
Observations	475	341
Adjusted R^2	0.329	0.378
F	232.43	208.08

This table shows the regression results for two linear regressions to establish the first stage of the two-stage-least-squares regressions with dataset A as can be found in table 4. F-statistics per regression is included and both have the necessary size for the two-stage-least-squares regressions. Standard errors are depicted in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C5 Post-treatment outcomes per treatment group dataset A

	Treatment group			
	LowGen	HighGen	Total	Test
N	241 (50.7%)	234 (49.3%)	475 (100.0%)	
Bonus surprised				
Not Surprised	75 (31.1%)	6 (2.6%)	81 (17.1%)	<0.001***
Somewhat Surprised	97 (40.2%)	49 (20.9%)	146 (30.7%)	
Very Surprised	44 (18.3%)	70 (29.9%)	114 (24.0%)	
Extremely Surprised	25 (10.4%)	109 (46.6%)	134 (28.2%)	
Redistributed 2	0.697 (0.460)	0.739 (0.440)	0.718 (0.450)	0.308
Amount redistributed 2	1.306 (1.127)	1.544 (1.101)	1.423 (1.119)	0.021*
Considered genetics 2				
No, I forgot about it	9 (3.7%)	1 (0.4%)	10 (2.1%)	<0.001***
No, I did not think it was relevant	149 (61.8%)	118 (50.4%)	267 (56.2%)	
Yes	83 (34.4%)	115 (49.1%)	198 (41.7%)	
Type				
Egalitarian	21 (8.7%)	22 (9.4%)	43 (9.1%)	<0.001***
Performance Meritocrat	85 (35.3%)	84 (35.9%)	169 (35.6%)	
Genetics-Compensating	40 (16.6%)	75 (32.1%)	115 (24.2%)	
Genetics Minimizer	50 (20.7%)	9 (3.8%)	59 (12.4%)	
Information Lacking	18 (7.5%)	17 (7.3%)	35 (7.4%)	
Information Distrusting	6 (2.5%)	13 (5.6%)	19 (4.0%)	
Non-Classified	21 (8.7%)	14 (6.0%)	35 (7.4%)	

Impact genetics	2.817 (2.243)	6.218 (2.599)	4.493 (2.961)	<0.001***
Control	7.154 (2.179)	6.098 (2.722)	6.634 (2.515)	<0.001***
Responsibility	7.959 (2.004)	7.141 (2.448)	7.556 (2.269)	<0.001***
Fairness	7.548 (2.210)	6.684 (2.466)	7.122 (2.376)	<0.001***
Impact effort	7.759 (1.926)	6.825 (2.355)	7.299 (2.196)	<0.001***
Environment	0.224 (0.418)	0.248 (0.433)	0.236 (0.425)	0.542
Personality	44.278 (27.187)	56.957 (24.497)	50.524 (26.636)	<0.001***
Mental health	54.693 (26.625)	64.282 (23.796)	59.417 (25.697)	<0.001***
IQ	53.154 (27.875)	65.632 (24.273)	59.301 (26.871)	<0.001***
BMI	44.788 (27.662)	55.479 (28.020)	50.055 (28.319)	<0.001***
Success fairness	4.755 (3.144)	4.432 (2.894)	4.596 (3.025)	0.244
Nature fairness	4.722 (3.199)	4.111 (3.006)	4.421 (3.117)	0.033*
Efficiency fairness	4.261 (3.053)	3.722 (2.557)	3.996 (2.829)	0.038*
Accuracy study	5.975 (2.554)	5.197 (2.987)	5.592 (2.800)	0.002**
Mathematical ability				
Extremely below average	4 (1.7%)	6 (2.6%)	10 (2.1%)	0.419
Below average	37 (15.4%)	39 (16.7%)	76 (16.0%)	
Average	113 (46.9%)	123 (52.6%)	236 (49.7%)	
Above average	74 (30.7%)	58 (24.8%)	132 (27.8%)	
Extremely above average	13 (5.4%)	8 (3.4%)	21 (4.4%)	

This table shows statistics for post-treatment variables for dataset A. There are four columns: LowGen separate, HighGen separate, a totals row and the p-value of the test for differences between the two treatment groups. For numerical variables linear regressions are used to obtain the p-value, for categorical variables this is a Person Chi-squared test. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). Redistributed 2 is a binary numerical variables where 1 represents someone who redistributed and 0 represents someone who did not redistribute. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table C6 Correlations of treatment, manipulation variables and mechanism variables dataset A

	HighGen	Impact genetics	Control	Respon-sibility	Fairness	Impact Effort	Succes fairness	Nature fairness	Efficiency fairness
HighGen	1.0000								
Impact genetics	0.5748 ***	1.0000							
Control	-0.2100 ***	-0.3324 ***	1.0000						
Respon-sibility	-0.1804 ***	-0.2786 ***	0.7239 ***	1.0000					
Fairness	-0.1819 ***	-0.3105 ***	0.5101 ***	0.5231 ***	1.0000				
Impact effort	-0.2130 ***	-0.3161 ***	0.5260 ***	0.5663 ***	0.4519 ***	1.0000			
Success fairness	-0.0535	0.0.05	0.1608 ***	0.2062 ***	0.3054 ***	0.1637 ***	1.0000		
Nature fairness	-0.0981 *	0.0035	0.1483 **	0.1858 ***	0.3200 ***	0.1924 ***	0.8142 ***	1.0000	
Efficiency fairness	-0.0954 *	0.0418	0.0947 *	0.1240 **	0.2150 ***	0.2111 ***	0.7527 ***	0.7700 ***	1.0000

This table shows pairwise correlations between the variables included. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table C7 Balance table of demographics dataset B

	Treatment group				
	Control	Factors	Genetics	Total	Test
N	49 (34.5%)	46 (32.4%)	47 (33.1%)	142 (100.0%)	
Gender					
Man	18 (36.7%)	23 (50.0%)	17 (36.2%)	58 (40.8%)	0.303
Woman	29 (59.2%)	21 (45.7%)	30 (63.8%)	80 (56.3%)	
Non-binary/genderfluid/other	2 (4.1%)	2 (4.3%)	0 (0.0%)	4 (2.8%)	
Age	30.143 (14.640)	33.326 (16.680)	31.702 (16.331)	31.690 (15.826)	0.622
Education					
High School	22 (44.9%)	13 (28.3%)	19 (40.4%)	54 (38.0%)	0.396
College (including MBO)	2 (4.1%)	8 (17.4%)	3 (6.4%)	13 (9.2%)	
Bachelor's Degree	13 (26.5%)	13 (28.3%)	14 (29.8%)	40 (28.2%)	
Master's Degree	9 (18.4%)	11 (23.9%)	9 (19.1%)	29 (20.4%)	
Doctorate or Professional Degree	3 (6.1%)	1 (2.2%)	2 (4.3%)	6 (4.2%)	
Political stance					
In the middle	15 (30.6%)	11 (23.9%)	11 (23.4%)	37 (26.1%)	0.719
Left	13 (26.5%)	12 (26.1%)	8 (17.0%)	33 (23.2%)	
Somewhat left	14 (28.6%)	13 (28.3%)	17 (36.2%)	44 (31.0%)	
Somewhat right	6 (12.2%)	7 (15.2%)	6 (12.8%)	19 (13.4%)	
Right	1 (2.0%)	3 (6.5%)	5 (10.6%)	9 (6.3%)	
income in two categories relative to median income (€39,100 in 2021 so close to					
€0 to €40,000	38 (82.6%)	34 (75.6%)	35 (76.1%)	107 (78.1%)	0.662
Over €40,000	8 (17.4%)	11 (24.4%)	11 (23.9%)	30 (21.9%)	
Religious activity in broader categories					
Never	30 (61.2%)	25 (54.3%)	25 (54.3%)	80 (56.7%)	0.321
Rarely	12 (24.5%)	17 (37.0%)	11 (23.9%)	40 (28.4%)	
Several times a month or more	7 (14.3%)	4 (8.7%)	10 (21.7%)	21 (14.9%)	

This table shows statistics for demographic variables for dataset B. There are five columns: Control, Factors, Genetics, a totals row and the p-value of the test for differences between the three treatment groups. For numerical variables linear regressions are used to obtain the p-value, for categorical variables this is a Person Chi-squared test. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). * p < 0.05, ** p < 0.01, *** p < 0.001.

Table C8 statistics on other variables dataset B

	Treatment group				
	Control	Factors	Genetics	Total	Test
N	49 (34.5%)	46 (32.4%)	47 (33.1%)	142 (100.0%)	
Any role genetics					
No, not at all	1 (2.0%)	1 (2.2%)	3 (6.4%)	5 (3.5%)	0.660
Yes, for a small part	25 (51.0%)	26 (56.5%)	23 (48.9%)	74 (52.1%)	
Yes, for a large part	23 (46.9%)	19 (41.3%)	20 (42.6%)	62 (43.7%)	
Yes, fully	0 (0.0%)	0 (0.0%)	1 (2.1%)	1 (0.7%)	
Heritability estimate	47.490 (20.275)	42.283 (21.969)	49.574 (21.185)	46.493 (21.206)	0.234
Type person					
Egalitarian	5 (10.2%)	11 (23.9%)	9 (19.1%)	25 (17.6%)	0.409
Performance Meritocrat	30 (61.2%)	24 (52.2%)	26 (55.3%)	80 (56.3%)	
Circumstances-Compensating	6 (12.2%)	4 (8.7%)	8 (17.0%)	18 (12.7%)	
Genetics Minimizer	2 (4.1%)	0 (0.0%)	0 (0.0%)	2 (1.4%)	
Information Lacking	1 (2.0%)	3 (6.5%)	2 (4.3%)	6 (4.2%)	
Non-Classified	5 (10.2%)	4 (8.7%)	2 (4.3%)	11 (7.7%)	
Impact genetics	4.633 (2.089)	4.283 (2.094)	5.021 (2.251)	4.648 (2.151)	0.255
Control	5.857 (1.979)	6.304 (2.269)	6.234 (2.315)	6.127 (2.183)	0.562
Responsibility	7.102 (1.782)	7.022 (2.595)	7.468 (2.052)	7.197 (2.154)	0.568
Fairness	6.898 (1.971)	6.630 (2.515)	5.936 (1.904)	6.493 (2.166)	0.081
Impact effort	6.102 (1.960)	6.630 (2.245)	6.766 (1.902)	6.493 (2.045)	0.244
Environment	1.286 (0.456)	1.348 (0.482)	1.362 (0.486)	1.331 (0.472)	0.705
Personality	56.184 (20.332)	54.261 (23.481)	54.787 (22.927)	55.099 (22.110)	0.909
Mental health	56.776 (20.805)	57.739 (20.728)	52.723 (20.775)	55.746 (20.736)	0.465
IQ	66.755 (19.481)	63.326 (21.531)	68.468 (20.188)	66.211 (20.363)	0.467
BMI	52.673 (24.757)	48.674 (24.010)	49.106 (26.991)	50.197 (25.171)	0.697
Succes fairness	4.347 (3.179)	4.761 (2.861)	4.809 (2.864)	4.634 (2.962)	0.705
Nature fairness	4.265 (2.892)	3.848 (3.190)	3.979 (2.642)	4.035 (2.899)	0.774
Efficiency fairness	3.776 (2.664)	4.326 (3.120)	4.532 (2.933)	4.204 (2.904)	0.420
Policies	7.571 (2.441)	7.957 (2.054)	7.553 (2.041)	7.690 (2.184)	0.606
Mathematical ability					
Extremely below average	0 (0.0%)	0 (0.0%)	1 (2.1%)	1 (0.7%)	0.666

Below average	5 (10.2%)	6 (13.0%)	3 (6.4%)	14 (9.9%)	
Average	21 (42.9%)	17 (37.0%)	16 (34.0%)	54 (38.0%)	
Above average	15 (30.6%)	19 (41.3%)	20 (42.6%)	54 (38.0%)	
Extremely above average	8 (16.3%)	4 (8.7%)	7 (14.9%)	19 (13.4%)	

This table shows statistics for several variables for dataset B. There are five columns: Control, Factors, Genetics, a totals row and the p-value of the test for differences between the three treatment groups. For numerical variables linear regressions are used to obtain the p-value, for categorical variables this is a Person Chi-squared test. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). * p < 0.05, ** p < 0.01, *** p < 0.001.

Table C9 Regression Results dataset B including only two treatment groups per regression

	Redistributed	Amount redistributed	Amount redistributed given redistributed	Amount redistributed, no Factors	Amount redistributed, no Control	Amount redistributed, no Genetics
Factors	0.0847	0.283	0.144			0.283
	(0.0967)	(0.238)	(0.156)			(0.237)
Genetics	0.0908	0.291	0.136	0.291	0.00786	
	(0.0959)	(0.234)	(0.151)	(0.234)	(0.244)	
Constant	0.633***	1.347***	2.129***	1.347***	1.630***	1.347***
	(0.0696)	(0.161)	(0.101)	(0.164)	(0.173)	(0.165)
Observations	142	142	98	96	93	95
Adjusted R^2	-0.006	-0.000	-0.010	0.006	-0.011	0.005

This table shows the regression results for six linear regressions with combined samples. Columns 4, 5 and 6 run the regression on Amount redistributed with only two treatment groups included. Columns 2 & 3 have the same dependent variable, but for column 3 only respondents who redistributed were selected. Factors and Genetics are dummy variables for treatment, with the Control group included in the constant, except for column 5 where Factors is included in the constant as respondents in the Control group were excluded. Redistributed is a binary variable where 0 represents a non-redistributing respondent, and 1 represents a respondent who did redistribute. Standard errors are depicted in parentheses.*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C10 statistics on demographic variables combined datasets

	Sample			
	Sample A	Sample B	Total	Test
N	475 (90.6%)	49 (9.4%)	524 (100.0%)	
Gender				
Male	178 (37.5%)	18 (36.7%)	196 (37.4%)	0.003**
Female	296 (62.3%)	29 (59.2%)	325 (62.0%)	
Other	1 (0.2%)	2 (4.1%)	3 (0.6%)	
Age	41.684 (14.303)	30.143 (14.640)	40.605 (14.710)	<0.001***
Education				
Less than High School	1 (0.2%)	0 (0.0%)	1 (0.2%)	<0.001***
High School	50 (10.5%)	22 (44.9%)	72 (13.7%)	
Some college	140 (29.5%)	2 (4.1%)	142 (27.1%)	
Bachelor's Degree	176 (37.1%)	13 (26.5%)	189 (36.1%)	

Master's Degree	83 (17.5%)	9 (18.4%)	92 (17.6%)	
Doctorate or Professional Degree	23 (4.8%)	3 (6.1%)	26 (5.0%)	
I prefer not to disclose	2 (0.4%)	0 (0.0%)	2 (0.4%)	
Political stance				
Left	253 (53.3%)	27 (55.1%)	280 (53.4%)	0.777
Middle	135 (28.4%)	15 (30.6%)	150 (28.6%)	
Right	87 (18.3%)	7 (14.3%)	94 (17.9%)	
Income				
Less than $10,000	60 (12.6%)		60 (11.5%)	<0.001***
$10,000 to $20,000	63 (13.3%)		63 (12.0%)	
$20,000 to $30,000	47 (9.9%)		47 (9.0%)	
$30,000 to $40,000	49 (10.3%)		49 (9.4%)	
$40,000 to $50,000	41 (8.6%)		41 (7.8%)	
$50,000 to $60,000	44 (9.3%)		44 (8.4%)	
$60,000 to $70,000	37 (7.8%)		37 (7.1%)	
$70,000 to $80,000	34 (7.2%)		34 (6.5%)	
$80,000 to $90,000	15 (3.2%)		15 (2.9%)	
$90,000 to $100,000	19 (4.0%)		19 (3.6%)	
Over $100,000	57 (12.0%)		57 (10.9%)	
Less than €10,000		17 (34.7%)	17 (3.2%)	
€10,000 to €20,000		16 (32.7%)	16 (3.1%)	
€20,000 to €30,000		3 (6.1%)	3 (0.6%)	
€30,000 to €40,000		2 (4.1%)	2 (0.4%)	
€40,000 to €50,000		1 (2.0%)	1 (0.2%)	
€50,000 to €60,000		2 (4.1%)	2 (0.4%)	
€80,000 to €90,000		1 (2.0%)	1 (0.2%)	
Over €100,000		4 (8.2%)	4 (0.8%)	
I prefer not to disclose	9 (1.9%)	3 (6.1%)	12 (2.3%)	
Religious activity				
Never	200 (42.1%)	30 (61.2%)	230 (43.9%)	0.058
Rarely	119 (25.1%)	12 (24.5%)	131 (25.0%)	
Several times a month	51 (10.7%)	0 (0.0%)	51 (9.7%)	
Once a week	57 (12.0%)	4 (8.2%)	61 (11.6%)	
Multiple times a week	39 (8.2%)	3 (6.1%)	42 (8.0%)	
I prefer not to disclose	9 (1.9%)	0 (0.0%)	9 (1.7%)	

This table shows statistics for demographics between datasets. There are four columns: Sample A, Sample B, a totals row and the p-value of the test for differences between the two samples. For numerical variables linear regressions are used to obtain the p-value, for categorical variables this is a Person Chi-squared test. For numerical variables it shows the mean (with standard deviation between brackets) and for categorical variables it shows frequency (with percentage within group between brackets). * p < 0.05, ** p < 0.01, *** p < 0.001.

Appendix D Notes on categorization into types

The categorization of respondents into types is based on Pogliano (2024), here further specification of the categories can be found. Note that the amount redistributed does not determine the type of person someone is.

Categories dataset A

The categories that respondents were categorized as in dataset A are the following, with a short description (Pogliano, 2024):

Egalitarian: They argue that an equal split is the most fair choice, claiming that equality should be a guiding principle.

Performance meritocrat: They do not care about genetics. They believe that the winner should be recognized and compensated no matter what.

Genetics-compensating meritocrat: They care about genetics, realizing that genetics made the starting playing field unequal. As such, they compensate for it by redistributing.

Genetics minimizer: They think genetics count too little to be taken into account, they claim other factors (such as hard work and education) affect performance much more.

Information lacking: They say that they do not know the extent to which genetics played a role in the scenario, as they have no information about the genetics of the two workers.

Information distrusting: They raise questions on whether the information provided was true or not. Alternatively, they say they do not trust it at all.

Non-classified: Any individual you cannot place in any of the other categories.

Categories dataset B

The following categories were changed:

- Genetics-compensating meritocrat was changed to Circumstances-compensating meritocrat. They compensate for differing circumstances that could have made the playing field unequal. Compensating for upbringing now matches this category, it did not match Genetics-compensating meritocrat in dataset A.
- Genetics minimizer was changed to Circumstances minimizer. They minimize the role of any type of circumstances, saying both workers had equal opportunities.
- Information distrusting does not apply as no specific information was provided to respondents.

This is done to create equal category possibilities per treatment group, and match the differing treatment.

Remarks on general data categorization

A lot of people redistributed just for workers having spent any time/effort on the task. These people still argued that the winner should earn the highest reward. Furthermore, they though that the losing worker should be compensated for the output they produced. Since these people rewarded effort, with the most for the winner, these people were classified under Performance meritocrat.

People stating that rewards should be performance based, but acknowledge other factors might have played a role in outcome, other than effort, were considered a Performance meritocrat, as the distributive decision was based on that, unless indicated otherwise.

Many people simply assumed all workers to have put in effort, without this being mentioned, showing an expectation of good faith.

It was not always clear how workers had been recruited and whether they knew the task would be mathematical.

Respondents equally distributing $3 to both workers because they contributed to the research were classified as Egalitarian since they believed that just by working they contributed. This might be different when not considering the research.

Some respondents compensated the loser for encouragement or to limit frustration for worker D.

Remarks on data categorization dataset A

People showed bad understanding of the heritability estimate, many people wrongfully interpreted it as being causal/deterministic.

People sometimes interpreted the genetic information as being intended to lead to higher pay-offs for the winner, sometimes leading to irritation towards the general research.

The question “Do you feel the information on genetics was relevant?” sometimes got interpreted whether they thought genetics to play a role on outcome, which made their answers not show their thought process behind their distributive choice.

The question: “Now we are interested in understanding the reasoning behind your choice for (not) redistributing the bonus. Please provide your motivation in 2 to 3 sentences.” got misinterpreted as people felt it implied that they did not redistribute when they did.

A few people interpreted genetics as fully being gender, sometimes leading to irritation towards the general research.

Remark on data categorization dataset B

Two respondents mentioned that awarding people based on performance in something they might not be good at (no matter circumstances), as judging a fish on its ability to climb a tree.

Appendix E Survey B[1]

Survey B starts at next page.

[1] For survey A, see Pogliano (2024).

Opening and consent

Thank you for taking interest in this survey. It will help gather knowledge on peoples' attitudes on fairness and distribution.

Your responses will be used strictly for academic purposes. All gathered data will be anonymous and non-sensitive (like age, income, etc.). We promise that your data will not be used for any purpose other than for this research topic directly.

Notice that you can withdraw your participation from this study by returning your submission, no data will be stored in that case. If you have any questions at any point, please contact us at 598836nz@student.eur.nl.

(P.S: This survey contains credits to get free survey responses at SurveySwap.io)

Please indicate that you understand and consent.

- ○ I consent

○ I do not consent

Demographics

Please, start by answering the following questions.

What gender do you identify as?

○ Man
○ Woman
○ Non-binary/genderfluid/other
○ I prefer not to disclose

What is your age?

What is the highest level of education you have completed?

○ Less than High School

- High School
- College (including MBO)
- Bachelor's Degree
- Master's Degree
- Doctorate or Professional Degree
- I prefer not to disclose

How would you describe your political views?

- Left
- Somewhat left
- In the middle
- Somewhat right
- Right

What was your total personal gross income last year? Take into account all your sources of income, including scholarships, health benefits, fringe benefits, and others. Please note that this is your personal income, not the income of your household.

- Less than €10,000
- €10,000 to €20,000
- €20,000 to €30,000
- €30,000 to €40,000

- ○ €40,000 to €50,000
- ○ €50,000 to €60,000
- ○ €60,000 to €70,000
- ○ €70,000 to €80,000
- ○ €80,000 to €90,000
- ○ €90,000 to €100,000
- ○ Over €100,000
- ○ I prefer not to disclose

How frequently do you participate in communal religious activities, such as attending religious services, prayer, or other religious gatherings?

- ○ Multiple times a week
- ○ Once a week
- ○ Several times a month
- ○ Rarely
- ○ Never
- ○ I prefer not to disclose

Intro and distribution factors

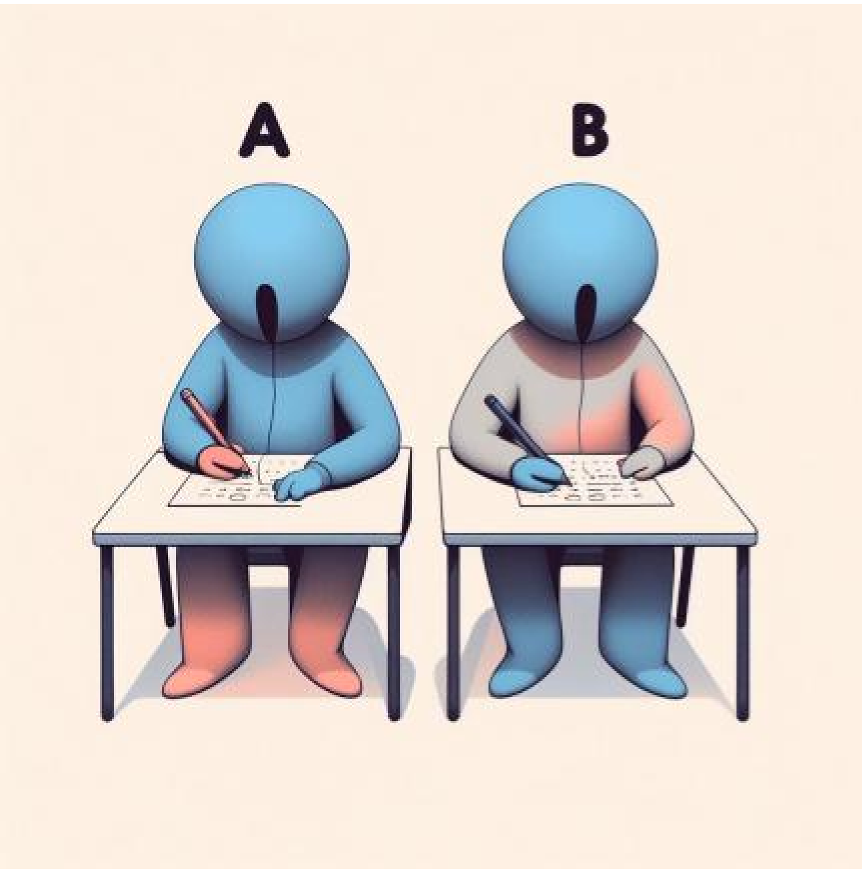
<u>Please read the instructions carefully. There will be a comprehension quiz later to ensure you</u>

understand the instructions.

Let there be the following (hypothetical) situation.

Last week two persons, person A and person B, were invited to conduct an assignment on an online platform. The persons did not know which type of assignment they had to complete. The assignment turned out to require **mathematical ability**.

Mathematical ability is the result of a **variety of factors.**



Each person was paid €1.25 for completing the assignment regardless of their performance. Person A and Person B were also informed they might receive some additional payment but they were not informed what that depended on.

To make sure you understood the information correctly, please answer the following questions. You will be able to continue to the next page once you have answered them correctly.

How much do the persons receive for completing the assignment?

- ○ €1.25
- ○ €1.25 and a known additional amount
- ○ €1.25 and an unknown additional amount

Which type of assignment do the persons complete?

- ○ Mathematical Assignment
- ○ Reading Assignment
- ○ Comprehension Assignment

Please take your time to make your decision.

Now you learn that person A completed more tasks correctly in the mathematical assignment than person B.

The research team considered assigning an **additional bonus of €6** to person A, since person A performed better. Person A and person B are **not** informed about this.

It is known that mathematical ability is the result of a **variety of factors.**

This is where you come into play. You can decide how to redistribute the bonus between Person A and Person B before they learn their payoffs. They will receive the final payoffs **determined by you** without further details.

How would you distribute the bonus?

Person A (won the bonus)	6
Person B (did not win the bonus)	0
Total	6

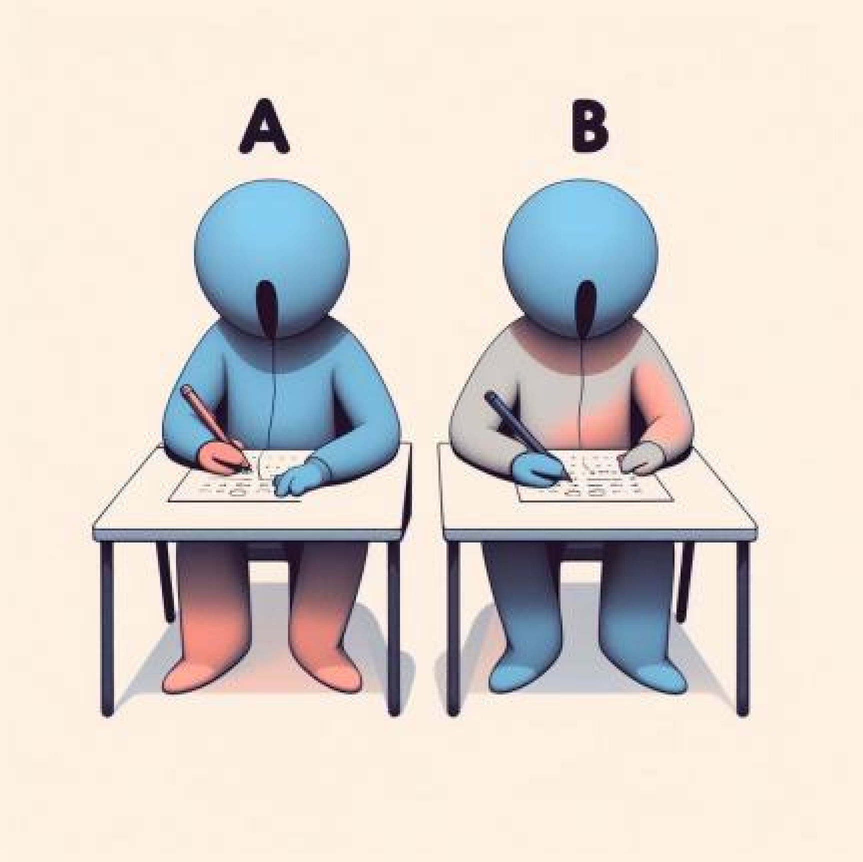
Intro and distribution genetics

Please read the instructions carefully. There will be a comprehension quiz later to ensure you understand the instructions.

Let there be the following (hypothetical) situation.

Last week two persons, person A and person B, were invited to conduct an assignment on an online platform. The persons did not know which type of assignment they had to complete. The assignment turned out to require **mathematical ability**.

Mathematical ability is the result of a **variety of factors**, one of which is **genetics.**



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How much do the persons receive for completing the assignment?

- €1.25
- €1.25 and a known additional amount
- €1.25 and an unknown additional amount

Which type of assignment do the persons complete?

- Mathematical Assignment
- Reading Assignment
- Comprehension Assignment

Please take your time to make your decision.

Now you learn that person A completed more tasks correctly in the mathematical assignment than person B.

The research team considered assigning an **additional bonus of €6** to person A, since person A performed better. Person A and person B are **not** informed about this.

It is known that mathematical ability is the result of a **variety of factors,** one of which is **genetics.**

This is where you come into play. You can decide how to redistribute the bonus between Person A and Person B before they learn their payoffs. They will receive the final payoffs **determined by you** without further details.

How would you distribute the bonus?

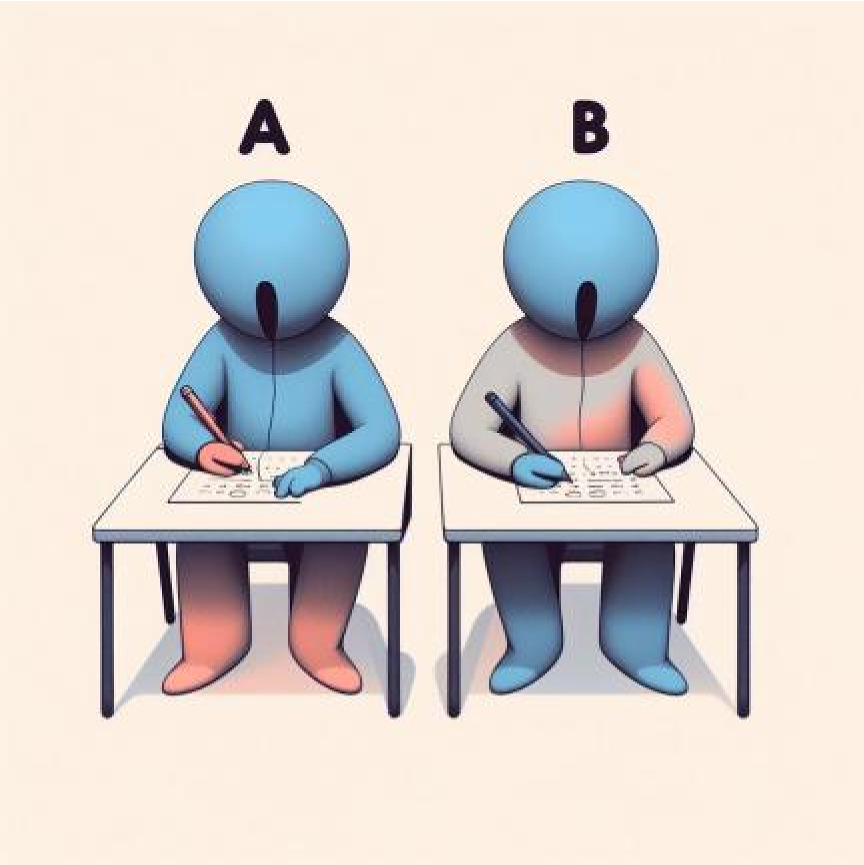
Person A (won the bonus)	6
Person B (did not win the bonus)	0
Total	6

Intro and distribution control

Please read the instructions carefully. There will be a comprehension quiz later to ensure you understand the instructions.

Let there be the following (hypothetical) situation.

Last week two persons, person A and person B, were invited to conduct an assignment on an online platform. The persons did not know which type of assignment they had to complete. The assignment turned out to require **mathematical ability**.



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To make sure you understood the information correctly, please answer the following questions. You will be able to continue to the next page once you have answered them correctly.

How much do the persons receive for completing the assignment?

- ○ €1.25
- ○ €1.25 and a known additional amount
- ○ €1.25 and an unknown additional amount

Which type of assignment do the persons complete?

- ○ Mathematical Assignment
- ○ Reading Assignment
- ○ Comprehension Assignment

Please take your time to make your decision.

Now you learn that person A completed more tasks correctly in the mathematical assignment than person B.

The research team considered assigning an **additional bonus of €6** to person A, since person A performed better. Person A and person B are **not** informed about this.

This is where you come into play. You can decide how to redistribute the bonus between Person A and Person B before they learn their payoffs. They will receive the final payoffs **determined by you** without further details.

How would you distribute the bonus?

Person A (won the bonus)	6
Person B (did not win the bonus)	0
Total	6

Role of Genetics

Do you believe that genetics play a role in influencing mathematical ability, and how much?

- Yes, fully
- Yes, for a large part
- Yes, for a small part
- No, not at all

Several studies have shown that **genetics** can influence many outcomes in people's lives, including **mathematical ability**.

To the best of your knowledge, how much of the difference in mathematical ability between people is due to **genetics**?

Enter the value as a **percentage**.

0 10 20 30 40 50 60 70 80 90 100

Did you consider the role of **genetics** (that is, the fact that genetics might have affected the performance of the people) when deciding how to distribute the bonus?

- Yes, and it affected my distribution
- Yes, but it did not change anything about my distribution
- No, I did not think about it

Open Question 1

Now we are interested in understanding the reasoning behind your choice of distribution of the bonus. Why did you (not) redistribute some of the bonus to person B? Why did you (not) consider genetics in this choice? Please provide your motivation in 2-4 sentences.

Manipulation Questions

Now think back at the question with persons A and B and answer the following questions.

How much did **genetics** impact the performance of the persons?

Not at all										Completely
0	1	2	3	4	5	6	7	8	9	10

How much **control** did the persons have over their performance?

They had no control										They had full control
0	1	2	3	4	5	6	7	8	9	10

How **responsible** were the persons for their performance?

Not responsible										Fully responsible
0	1	2	3	4	5	6	7	8	9	10

How **fair** do you think it was that person A had a better performance?

Extremely unfair — Extremely Fair

0○ 1○ 2○ 3○ 4○ 5○ 6○ 7○ 8○ 9○ 10○

How much did **effort** impact the performance of the persons?

Not at all — Completely

0○ 1○ 2○ 3○ 4○ 5○ 6○ 7○ 8○ 9○ 10○

Did you think about the environment the persons grew up in when redistributing?

○ Yes

○ No

External

Now please answer the following questions.

To the best of your knowledge, how important do you think **genetics** is in influencing the following traits? (0 means that genetics plays no role, 100 means that genetics fully determines the trait)

	0	10	20	30	40	50	60	70	80	90	100	
Personality												
Mental Health												
IQ												
Body Mass Index												

MEC

Now, please indicate how much you agree with the following statements (0 means you completely disagree, while 10 means that you completely agree).

	0	1	2	3	4	5	6	7	8	9	10
Inequality coming from genetics is fair because everyone has some genetics that can make them successful.	○	○	○	○	○	○	○	○	○	○	○
Inequality coming from genetics is fair because genetics are given by nature.	○	○	○	○	○	○	○	○	○	○	○
Select a value of 1 to ensure you are reading this attentively.	○	○	○	○	○	○	○	○	○	○	○

	0	1	2	3	4	5	6	7	8	9	10
Inequality coming from genetics is fair because it contributes to the efficiency of society.	○	○	○	○	○	○	○	○	○	○	○
The government should create policies and an environment that gives everyone a chance to do well in society, no matter genetics.	○	○	○	○	○	○	○	○	○	○	○

Mathematical Ability

Finally, answer this last question.

How do you rate your mathematical ability?

- Extremely below average
- Below average
- Average
- Above average
- Extremely above average