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# The ICT Revolution and Preferences for Taxing Top Earners*

David Hope† Julian Limberg‡ Nina Weber§

**Abstract**

How has the ICT-driven transformation of labour markets in recent decades affected redistributive preferences? We move beyond existing research by focusing on the 'winners' of the ICT revolution and on other-regarding preferences for taxing top earners. We carry out an interactive, online experiment with around 3,000 US respondents to test whether fairness perceptions and redistributive preferences differ when top incomes are gained through luck, routine work, or complex work. This set up aims to mirror the changing nature of tasks performed by high-earning workers in the US labour market as a result of the ICT revolution. We find that the desired tax rate on top earners is up to 5.3 percentage points lower for the complex work than the routine work treatment, and that high incomes from complex work are perceived as fairer and more deserved. A follow-up vignettes study then provides strong evidence that high earning jobs are perceived to be more complex. Taken together, our findings highlight an important and previously under-explored channel through which the ICT revolution may have dampened demand for progressive taxation in the advanced democracies.

Keywords: ICT revolution; labour markets; redistributive preferences; tax policy

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# 1 Introduction

The information and communications technology (ICT) revolution has transformed labour markets in the advanced capitalist democracies in recent decades. An influential body of work in labour economics has shown that jobs focused on routine tasks have been increasingly replaced by computers and robots, while at the same time, jobs focused on the type of complex, non-routine cognitive tasks that are complementary to new technologies have significantly expanded (Acemoglu & Autor, 2011; Autor, Levy, & Murnane, 2003; Caines, Hoffmann, & Kambourov, 2017; Goos, Manning, & Salomons, 2009). The ICT revolution has therefore resulted in a large increase in demand for skilled (i.e., college-educated) workers since the 1980s (Goldin & Katz, 2010), and has been clearly linked to both the rise in the college wage premia (Autor, 2014; Autor, Katz, & Kearney, 2008) and the concentration of income at the very top of the ladder (Hope & Martelli, 2019; Kaplan & Rauh, 2013).

This research has stimulated a growing body of work in political science exploring the implications of this major technological transformation for political and policy preferences (see Gallego and Kurer 2022 for an extensive review). Workers at greater risk of automation (i.e. being replaced by computers or machines) have been found to be more supportive of mainstream left (Gingrich, 2019) and populist right parties and candidates (Anelli, Colantone, & Stanig, 2021; Frey, Berger, & Chen, 2018; Gingrich, 2019; Kurer, 2020). Recent studies analysing cross-national survey data have also shown that workers more exposed to technology-induced job loss are more supportive of policies to slow the pace of technological change (Gallego, Kuo, Manzano, & Fernández-Albertos, 2022) and to redistribute income from the rich to the poor (Busemeyer & Sahm, 2021; Thewissen & Rueda, 2019).

Given the clear links this literature has drawn between the ICT revolution and demand for redistribution, it is puzzling that the rise of the knowledge economy in the advanced democracies has been so strongly associated with falling taxes on the rich (Hope & Limberg, 2022). A key part of unpicking this puzzle is that the existing political science literature has focused overwhelmingly on the 'losers' from the recent wave of technological change—i.e., workers in routine occupations that are exposed to automation. A couple of recent exceptions have started to unpack the political behaviour of the beneficiaries of the ICT revolution (Gallego, Kurer, & Schöll, 2022; Schöll & Kurer, 2023), but these analyses do not look at redistributive preferences. The other weakness of this literature in explaining falling tax progressivity in an era of rapid technological change is that it entirely focuses on self-interested preferences for redistribution, when preferences for taxing top incomes have been shown to be much more driven by other-regarding preferences; in particular, the extent to which high incomes are seen to be deserved and income differentials are considered fair (Hope, Limberg, & Weber, 2023; Limberg, 2020; Stantcheva, 2021).

In this paper, we aim to fill this gap in the literature looking at how the ICT revolution has changed the complexity of the work that top earners undertake and how this has fed into (other-regarding) preferences for redistribution. More specifically, we provide a first experimental test of whether fairness views and preferences for taxing top earners differ when their incomes are gained through luck, routine work, or (non-routine) complex work. If high incomes are increasingly being earned through more complex, analytical tasks (as a lot of empirical evidence shows—e.g., Caines et al. 2017; Philippon and Reshef 2012) and this leads to inequalities being perceived as fairer, this could provide an important new demand-side explanation for the substantial fall in the progressivity of tax systems in the advanced democracies since the 1980s (Emmenegger & Lierse, 2022; Hope & Limberg, 2022; Saez & Zucman, 2019).

Our empirical analysis centres on an interactive, online experiment with around 3,000 participants in the United States. In the experiment, workers are randomly allocated into groups of five across three treatment arms. Five dollars is allocated to one member of each group, and the allocation is decided either through luck (random allocation), performance on a routine slider task, or performance on a complex problems task. Our complex work treatment is specifically designed to replicate the type of cognitive, non-routine work that has become so richly rewarded in contemporary labour markets following the ICT revolution. We then give both the workers and a set of impartial spectators (who did not take part in the first stage of the experiment and have no material stake in the decision) the opportunity to tax the top earner and redistribute to the other members of the group. Our design therefore allows us to isolate whether the changes in preferences for taxing top earners across treatments are driven by material (self-)interest or by other-regarding preferences (similar to the approach used in Cappelen, Moene, Sørensen, and Tungodden 2013). We also complement our central experiment with an additional vignettes study, which tests whether people perceive high-earning jobs to be more complex.

The key finding of our central experiment is that impartial spectators preferences for taxing top earners crucially depend on the type of work being performed. The desired tax rate on top earners in the complex work treatment is 5.3 percentage points lower than in the routine work treatment. When looking at the workers, whose payoffs are directly affected by the redistributive decision, we do not see significant differences in preferences for taxing top earners between the routine and complex work treatments. This suggests that the difference between the routine and complex work treatments in the preferred tax rate on top earners is mostly driven by other-regarding preferences.

A causal mediation analysis shows that the mechanism linking increased work complexity to lower redistributive demands among impartial spectators appears to be a widely-held (and acted upon) belief that inequalities are fairer and top earners more deserving when incomes are gained through complex rather than routine work. This is driven by spectators believing that more effort and skill are required to perform well in complex work. The results from our follow-up vignettes study then provide strong evidence that high earning jobs are widely perceived to be more complex than jobs with lower earnings.

The paper makes an important new contribution to the literature on the consequences of the recent wave of technological change for redistributive preferences (as summarised in Gallego and Kurer 2022), as it shifts the focus onto the 'winners' of the transformation and provides new causal evidence on how the desire to tax their high incomes is heavily influenced by the perceived complexity of their work. It also furthers the growing body of research on voters' preferences for taxing the rich (Barnes, 2022; Emmenegger & Marx, 2019; Hope et al., 2023; Limberg, 2020; Stiers, Hooghe, Goubin, & Lewis-Beck, 2022), by making a strong case that focusing on other-regarding preferences is essential if we hope to better understand public support for taxing top earners in the knowledge economy.

The rest of the article proceeds as follows. Section 2 reviews the relevant literature and sets out our theory. Section 3 describes our experimental design. Section 4 presents the main results of our experiment, as well as an exploration of the mechanisms at work. Section 5 then presents the results of our follow-up vignettes study. Lastly, we provide some concluding remarks in Section 6.

# 2 The ICT Revolution and Policy Preferences

Labour markets in the advanced capitalist democracies have changed fundamentally in the last few decades. One of the most important drivers of this change has been the rapid advance of information and communications technologies (Acemoglu & Autor, 2011; Autor et al., 2003; Goos et al., 2009). In this section, we discuss the potential implications of this development for redistributive preferences. We start by looking at the literature that has investigated the effect of automation risks on political preferences. Based on this existing work, we then construct our argument about the relationship between the changing nature of work in the knowledge economy and other-regarding preferences for taxing top earners.

## 2.1 Automation Risks

How has the ICT revolution affected preferences for redistributive policies? In recent years, several studies have started to explore this question empirically (Busemeyer & Sahm, 2021; Dermont & Weisstanner, 2020; Gallego, Kuo, et al., 2022). This work has mostly focused on the role of automation risks (i.e. the risk of workers' jobs being replaced by computers or robots) (Jeffrey, 2021; Thewissen & Rueda, 2019). The general idea is straightforward: people who face economic risks are more likely to support policies that insure them against the materialisation of these risks (Hacker, Rehm, & Schlesinger, 2013; Moene & Wallerstein, 2001; Varian, 1980). Hence, individuals who face greater risks tend to show more support for redistributive policy measures.

The general literature on the political economy of risks has looked at a variety of different sources of risk that might induce appetite for redistribution, e.g. skill specificity (Iversen & Soskice, 2001), globalisation (Walter, 2010), and occupational unemployment rates (Rehm, 2009, 2011). The diffusion of ICT through the economy is an additional source of labour market risk because it raises the prospect of job loss for employees with high levels of routine task intensity (RTI). Simply put, tasks with a high RTI face the highest risk of automation (i.e. being replaced by computer-based technology), as they can be more easily replicated by computers or machines. For instance, Thewissen and Rueda (2019) use data from the European Social Survey and find that RTI is highly correlated with demands for redistribution. This link is particularly strong for high earners, who are at risk of losing more income.

Researchers have expanded the work on the effects of automation risks on policy preferences in at least three ways. First, some scholars have called for a differentiation between actual and perceived automation risks. Disentangling these two is crucial as individuals might be misinformed about their individual risk exposure. For instance, Kurer and Häusermann (2022) find that although RTI is correlated with perceived automation risk, it is far from being an ideal predictor. Second, scholars have started to differentiate between types of redistributive policies instead of looking at general attitudes towards redistribution. Most notably, studies have investigated the connection between automation risks and compensatory policies, such as unemployment insurance, as well as social investment policies such as retraining programmes (Busemeyer, Gandenberger, Knotz, & Tober, 2022; Jeffrey, 2021). Furthermore, following the general rise of studies looking at trade-offs between different policies (Bremer & Bürgisser, 2022; Häusermann, Kurer, & Traber, 2019), scholars have started to take these trade-offs into account when gauging the consequences of automation risks (Busemeyer & Tober, 2023). Third, recent studies use experimental or quasi-experimental evidence to shed more light on the causal relationship. For example, Jeffrey (2021) uses an information-provision survey experiment to increase individuals' perceived risk of job loss due to automation. She finds this has no effect on support for most redistributive policies. Her findings also show, however, that informing respondents about potential job losses due to automation using more political rhetoric can induce treatment effects.

Taken together, the existing work has highlighted the important role of automation risks for policy preferences. Yet, this work has at least two limitations. First, it solely looks at potential losers of the recent wave of technological change. With some notable exceptions (see, e.g., Gallego, Kurer, and Schöll 2022), most of this work is interested in those facing potential income losses due to automation. Research in labour economics, however, has clearly shown that the ICT revolution has also created a large pool of 'winners' (Acemoglu & Autor, 2011; Autor et al., 2003; Goldin & Katz, 2010). Second, existing studies almost exclusively focus on self-regarding preferences. As a consequence, we know very little about how the ICT revolution has shaped other-regarding preferences for redistribution (Dimick, Rueda, & Stegmueller, 2018).

## 2.2 The Winners of the ICT Revolution and Other-Regarding Preferences

Expanding existing work on the impact of the ICT revolution on redistributive preferences, we focus on attitudes towards taxing top earners. More precisely, we posit that the ICT-driven transformation of contemporary labour markets has affected other-regarding preferences for taxing those at the top of the income distribution. If high earners are perceived as more deserving of their high incomes due to the (growing) complexity of their work, then this may suppress demand for taxing high incomes.

Who are the winners of the ICT revolution? Technological advancements in recent decades have gone hand-in-hand with the rise of the knowledge economy, i.e. the transition from Fordist systems of mass production to service sector-dominated economies increasingly centred around ICT and college-educated workers (Acemoglu & Autor, 2011; Goldin & Katz, 2010; Hope & Martelli, 2019; Iversen & Soskice, 2019). As a consequence, top earners are increasingly performing more complex, analytical work that covers a wider array of different tasks adjacent to advances in information and communications technologies (Autor et al., 2003; Caines et al., 2017; Goos et al., 2009; Philippon & Reshef, 2012).[1]

Many studies on attitudes towards progressive taxation of top income earners stress the role of other-regarding preferences (Limberg, 2020; Stantcheva, 2021). The idea is straightforward: rather than individual income maximisation, perceptions of other individuals determine preferences. Thus, support for taxing top earners will be lower when their income is perceived as deserved and fair. An array of observational and experimental studies have identified the role of such other-regarding preferences in driving support for redistributive policies (Ackert, Martinez-Vazquez, & Rider, 2007; Alesina & Angeletos, 2005; Hope et al., 2023). For instance, scholars have found that demand for progressive taxation is higher when people think that high incomes are the result of luck rather than hard work or merit (Durante, Putterman, & van der Weele, 2014). Furthermore, appetite for top income taxation is higher when people believe that the rich were treated preferentially by the state (Scheve & Stasavage, 2016, 2021).

One of the main shortcomings of theories stressing the role of other-regarding preferences is that they are rather static. These theories are powerful tools to explain differences in tax policy preferences across individuals, but they struggle to explain

[1]The labour economics literature focusing on changing task inputs as a result of computerisation, often referred to as routine-biased technological change, directly developed out of the earlier literature on skill-biased technological change (e.g., Acemoglu 2002; Katz and Murphy 1992). While based on similar underlying economic models, there are some small differences between the approaches, especially concerning the expected effects of computer technologies on the middle of the income distribution. Crucially for our study, however, both approaches are aligned when it comes to the upper part of the income distribution, which is the focus of our central interactive, online experiment. The approaches both argue the complementarities between ICT technologies and high skills have dramatically increased demand for college-educated labour in recent decades, as well as markedly changing the nature of work for top earners.

why perceptions of deservingness and fairness, as well as tax policy instances, might change over time.[2] Most importantly, top income tax rates have fallen strongly in the last few decades, but the public backlash against this development was relatively muted. We posit that the changing nature of job tasks for high earners in the labour market as a result of the ICT revolution can help to explain this puzzle. If high income earners are seen as more deserving as ICT has increased the complexity of their work, this might account for suppressed demand for redistributive taxation. In other words, the high incomes of the winners from the ICT revolution, who excel at performing more complex tasks, might be perceived as fairer than the winners in Fordist production systems, where routine tasks were more central. Accordingly, demands for taxing high incomes generated from performing complex tasks should be lower than demands for taxing high incomes generated from performing routine tasks. This would align with existing studies on changing beliefs of meritocracy (Mijs, 2021), as well as with work the macro level showing that the rise of the knowledge economy has been strongly associated with falling tax rates on the rich (Hope & Limberg, 2022).

# 3 Experimental Design

In the previous section, we posited that the recent wave of technological change may have altered other-regarding preferences for taxing top incomes. More specifically, the changing nature of work for top earners as a result of the ICT revolution might affected the desire of others to tax them. If high incomes received through complex work are perceived as fairer and more deserving, then appetite for taxing the high earners will be lower. To test this theoretical proposition, we conduct an interactive, online experiment in the United States.

In the first stage of the experiment, workers are randomly assigned to one of our three treatment conditions and then put into groups of five. In the luck treatment,

[2] The work by Scheve and Stasavage (2016) is a notable exception as they show how warfare can lead to changing fairness perceptions.

one of the five workers is randomly allocated an initial bonus of $5. In the routine work treatment, workers each complete a simple slider task (Gill & Prowse, 2012) for three minutes. Here, the worker who completes the most sliders within each group receives an initial bonus allocation of $5. In the complex work treatment, each worker completes complex problems for three minutes. The worker who completes the most problems correctly within each group then receives an initial bonus allocation of $5. These problems consist of an even mix of math exercises (Niederle & Vesterlund, 2007), Raven's progressive matrices (Raven, 2000), and anagrams (Charness & Villeval, 2009). We purposely choose a mix of different types of problems to capture the non-routine nature of the type of work we are interested in. By dividing the complex work treatment into short individual problems, we are also able to estimate individual performance in a comparable manner to the routine work treatment.

The problems we utilise for the complex work treatment are specifically selected to mirror the type of abstract, problem-solving tasks that have become so highly valued at the top end of the US labour market since the ICT revolution. In the seminal labour economics paper on changing work tasks in the US economy as a result of computerisation (Autor et al., 2003), the authors show that labour input across the economy has shifted dramatically toward more complex, non-routine cognitive tasks since the 1970s. They also provide empirical evidence that these task shifts have taken place across a wide range of industries and occupations, that they are especially pronounced in the parts of the economy that have computerised more rapidly, and that they have mainly benefitted college-educated labour in the upper part of the income distribution.[3]

In the second stage of the experiment, both the workers and a set of impartial

[3] Autor et al. (2003) split non-routine cognitive tasks into non-routine analytical tasks and non-routine interactive tasks. Our complex work treatment fits more closely with non-routine analytical tasks as these are easier to replicate in an interactive, online experiment. Autor et al. (2003) show a lot of empirical evidence, however, that non-routine analytical tasks and non-routine interactive tasks have expanded in lockstep in the US labour market in recent decades as a result of computerisation, as both are strongly complementary to ICT. They also show that both types of tasks have become increasingly central to high-paying jobs across a wide range of occupations and industries in the US. Our complex work treatment therefore captures a crucial common feature of the shift towards more complex tasks that occurred for top earners across the US economy as a result of the ICT revolution.

spectators (who have no material interest in the decision they make) are provided with information on the initial $5 bonus allocation within their group. They are then able to propose a reallocation of the $5, to be divided equally between the other group members. While workers only make one distributive choice for their own group, spectators make three decisions. Each of these three decisions is for a group of workers in a different treatment condition. The order in which spectators see these three groups is randomised. For each group, there is then a 50% chance that the decision of one of three impartial spectators will be implemented[4] and a 50% chance that the decision of one of the five workers will be implemented. This setup, in which spectators and workers each face a 50% chance of having their preferences implemented, allows us to elicit incentivised preferences for both groups of subjects in all groups.

In the final part of the experiment, we elicit beliefs and preferences aimed at understanding the underlying mechanisms for the decisions subjects make.

Our experimental design contains two important features that are specifically chosen to align with our theoretical focus on top earners and other-regarding preferences. First, the use of impartial spectators, which is common in the experimental economics literature on distributive preferences (e.g. Cappelen et al., 2013), allows us to isolate other-regarding preferences as spectators have no material (i.e., self) interest in the redistributive choices they make (as only the workers receive any of the income that is redistributed). Second, we ask spectators to decide on an allocation of income for groups of five rather than pairs of workers (as is the more typical approach in the literature). This allows us to test preferences for taxing the incomes of top earners more directly.

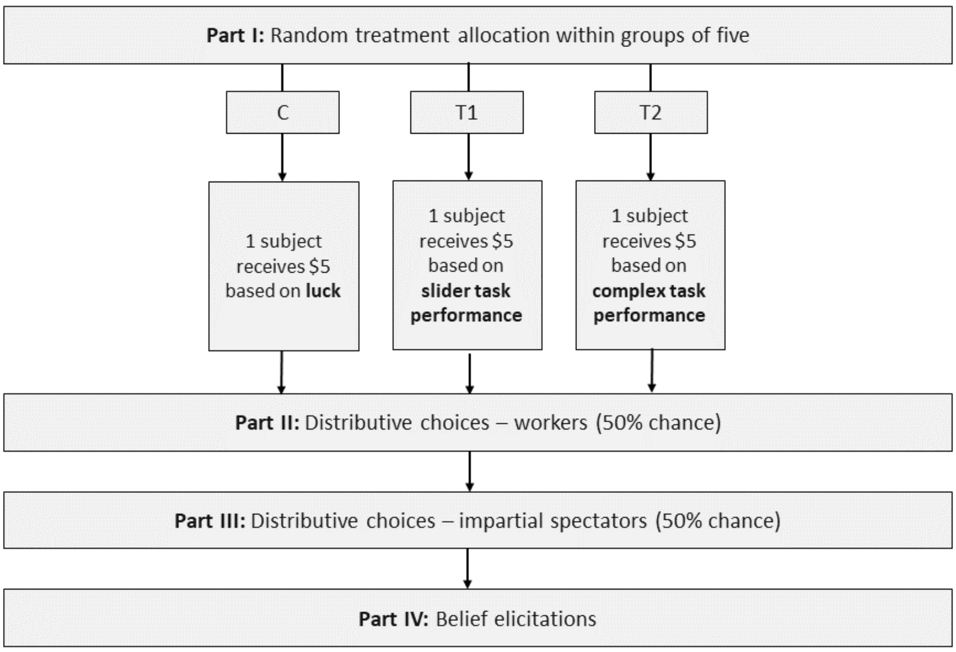
Our experiment aims to understand how people assess the changing complexity of work in the labour market as a result of the ICT revolution. We therefore use a within-subject design, whereby each spectator makes decisions in all three treat-

[4]Each spectator makes allocation decisions in all three treatment conditions but only one of their decisions will potentially be implemented. Therefore, three spectators are matched with each worker group and one spectator decision is selected at random to have a 50% chance of implementation.

ment conditions. We do this as it better matches the real-world assessments we are interested in understanding than a between-subject design. When people assess the fairness of incomes earned through complex work in the real world, they do so by comparison to other types of work and not in isolation. This is what we aim to capture in our experiment. A within-subject design also has the advantage that it allows us to estimate individual-level, and not just average, treatment effects. Finally, recent experimental evidence suggests that concerns about demand effects in online experiments might be exaggerated, which is usually the main concern raised about within-subject designs (Mummolo & Peterson, 2019).

Figure 1 provides an overview of the experimental design. In the remainder of the section, each part of the experiment will be explained in more detail. The full experimental instructions are set out in Part G of the Online Appendix.

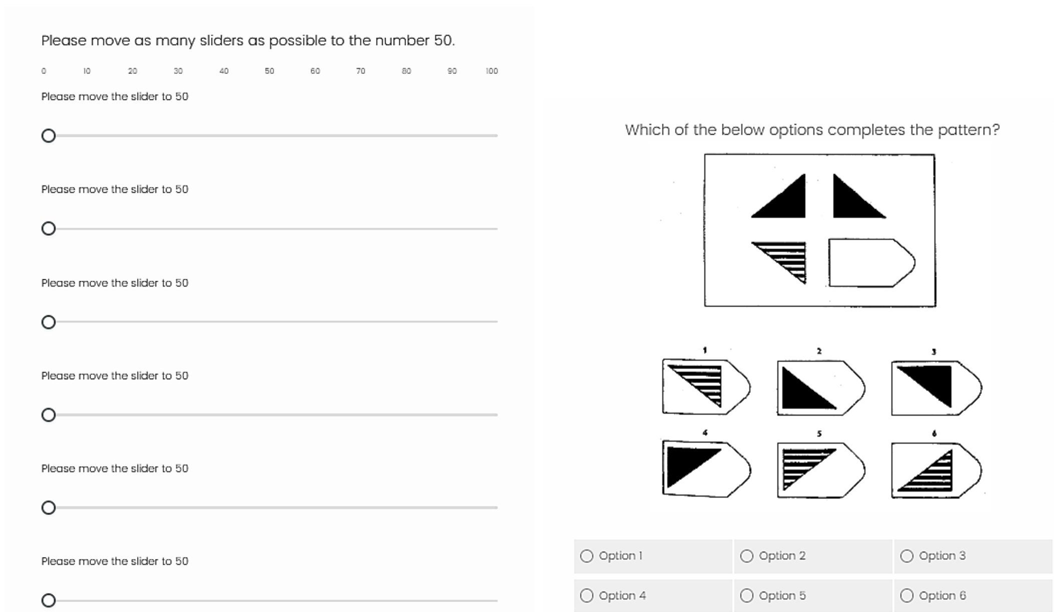
Figure 1: Experimental Design



## 3.1 Part I: Work Stage

The first part of the experiment consists of the work stage. Here, workers are randomly assigned to the luck, routine work, or complex work treatment. They are then randomly allocated to a group of five. Each worker within the group has been allocated to the same treatment. While workers in the luck treatment are simply told that the bonus will be allocated to one randomly selected worker, those in the routine and complex work treatments are asked to do a task for three minutes. Figure 2 illustrates examples of tasks workers faced in each treatment condition. The example shown for the complex work treatment is a Raven's progressive matrix, which is only one of the three different types of tasks workers face in randomised order during the work stage (examples of the other two complex tasks are shown in the experimental instructions in Part G of the Online Appendix).

Figure 2: Example Worker Screens




*Note:* The screen on the left was displayed to workers in the routine work treatment group. The screen on the right shows an example task workers faced in the complex work treatment group.

The randomly chosen worker (in the luck treatment) or the best performer (in the routine and complex work treatments) is allocated an initial bonus of $5. This amount will, however, only be paid after the decisions in part II and III are made and the beliefs in part IV are elicited.

### 3.2 Part II: Worker Distribution Stage

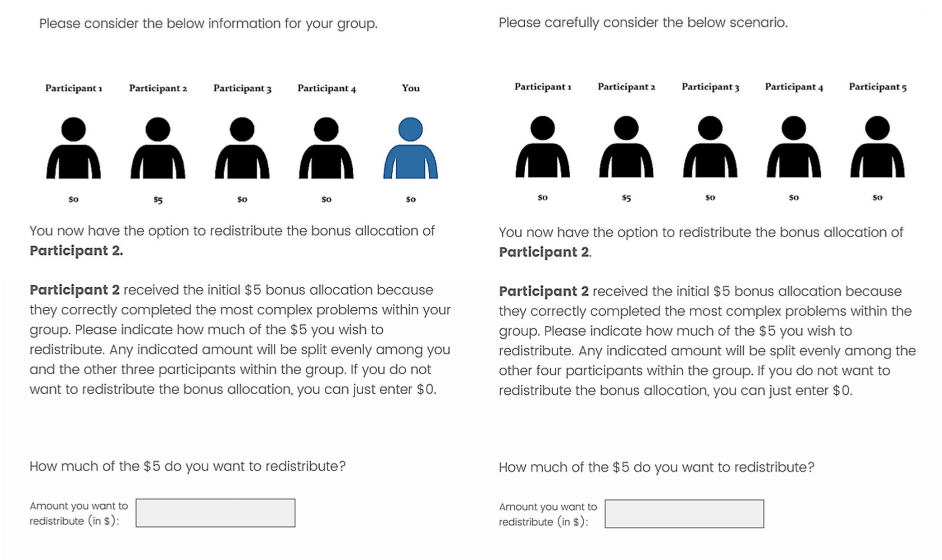
Workers are provided with the payoff information for their group (i.e., which group member was allocated the $5). Prior to making their distributive choice, workers are asked four understanding questions and are provided with the correct answers for each question before being able to proceed. They then have the option to redistribute the $5 allocated to the top earner, to be equally distributed across the other group members. Given there is a 50% chance the decision of one of the five workers will be implemented and that worker is chosen at random, there is a 10% chance an individual worker's decision will be implemented. The left panel in Figure 3 illustrates an example decision scenario for a worker who is not herself a top earner in the complex work condition.

### 3.3 Part III: Spectator Distribution Stage

After workers have completed their part of the experiment but prior to payment of the bonus allocations, spectators each make three allocation decisions, one for each treatment. The order in which they make decisions across the three treatments is randomised. For the routine and complex work decisions, spectators are asked to participate in the respective task themselves for one minute without being informed of their own performance. This stage aims to provide spectators with a better idea of the complexity of each task and allows us to compare spectator and worker decisions while holding task experience constant.

Prior to making their distributive choice, spectators are also asked four understanding questions and are provided with the correct answers for each question before being able to proceed. For each treatment, spectators are then provided with the payoff information for a group and have the option to redistribute the $5 allocated to the top earner, to be equally distributed across the other group members. There are three spectators for each group and a 50% chance the decision of one of the three spectators will be implemented. As that spectator is chosen at random, there is a 17% chance an individual spectator's decision will be implemented. Spectators receive no information on the preferences expressed by the workers in part II. The right panel in Figure 3 illustrates an example decision scenario for a spectator in the complex work condition.

Figure 3: Example Distribution Screens




*Note:* The left panel shows a distribution screen for a worker and the right panel shows a distribution screen for an impartial spectator.

### 3.4 Part IV: Belief Elicitations

To determine the underlying mechanisms for potential differences in redistributive choices across treatments, we elicit spectator and worker beliefs. We then end the experiment by asking a series of demographic questions. For spectators, the treatment-specific beliefs are elicited after each of the three decisions. We also include three incentivised belief elicitations, which are explained in detail in Part F of the Online Appendix.

The main experiment was conducted via Prolific Academic between the 14th and

25th of July 2022 with a total sample size of 519 spectators and 2,366 workers.[5] Our experimental design and the following analysis were pre-registered via the American Economic Association's registry for Randomized Controlled Trials with the reference ID AEARCTR-0009719. The average time subjects took to complete the experiment was 12 minutes for workers and 18 minutes for spectators. The average earnings of workers was $2.79 and the average earnings of spectators was $2.59. This corresponds to an average hourly rate of about $14 for workers and $9 for spectators.

# 4 Results

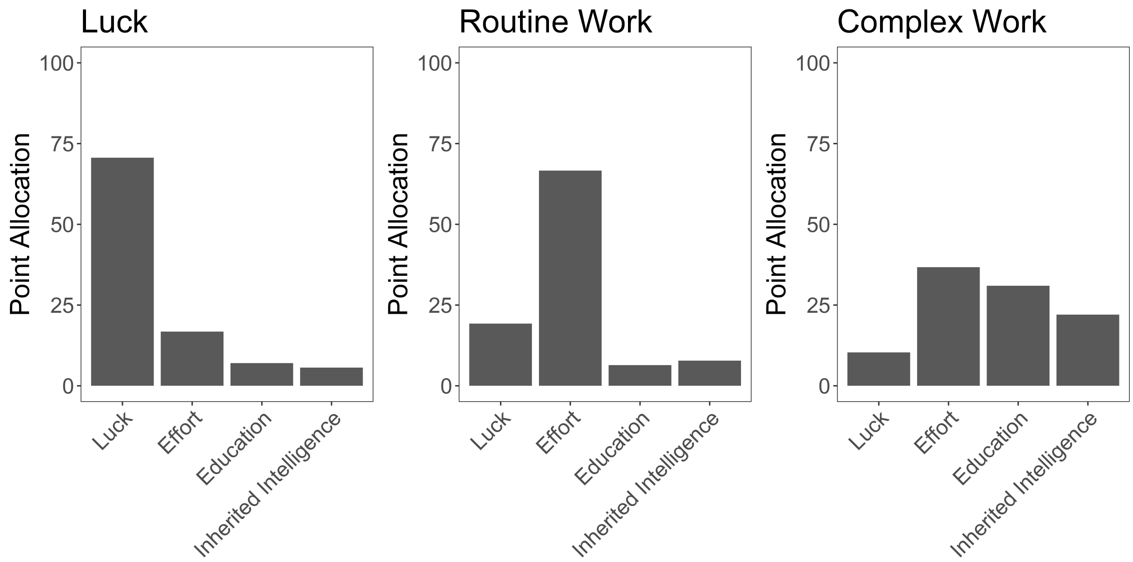
## 4.1 Perceptions of Treatments

In this section, we present the results of our main experiment. First, we are interested in individuals' perceptions of our treatments. More specifically, we asked respondents what they think matters for performance across the treatments. Participants allocated 100 points to 4 different options – luck, effort, education, and inherited intelligence. Figure 4 shows the point allocation by treatment condition. In line with the basic premise of our experiment, we see that the pattern of allocated points varies distinctively between treatments. As expected, luck is indeed perceived as the dominant aspect for receiving the bonus for the luck treatment. In contrast, participants see effort as the most important aspect for the routine work treatment. Both findings are in line with the existing experimental literature, which has used similar treatments. Importantly, respondents do not solely associate doing well in our complex work treatment with simple effort. Instead, they assign a diverse set of different characteristics to the treatment. Alongside effort, respondents also see education and inherited intelligence as central for performance in complex tasks. Crucially, these factors are also highly important in contemporary labour markets that have been transformed by the ICT revolution. Overall, these findings show strong support for our assumption that our

[5] Due to some workers dropping out between the work and distribution stages, these numbers do not correspond directly to the numbers stated in our pre-analysis plan.

treatments clearly differentiate between luck, routine work, and complex work.

Figure 4: Perceptions of What Matters for Performance Across Treatments




*Note:* Point allocation based on question "Why do you think [some perform well on the task participants in this group completed]/[one participant received the initial allocation of the $5 bonus]? Please allocate a total of 100 points across the below four options. Please ensure that the more points you allocate to an option, the more important you consider it to [be able to perform well on the task]/[receive the initial allocation of the $5 bonus]. Please allocate all 100 points before proceeding."

## 4.2 Redistributive Preferences

We now turn to the effects of the treatments on redistributive preferences. Recall that respondents had the possibility to take away up to $5 from the top earner and distribute it evenly among the other workers. We rescale this measure into a tax rate, with $5 resulting in a tax rate of 100% for top earners, and $0 resulting in a tax rate of 0%. We estimate the following model:

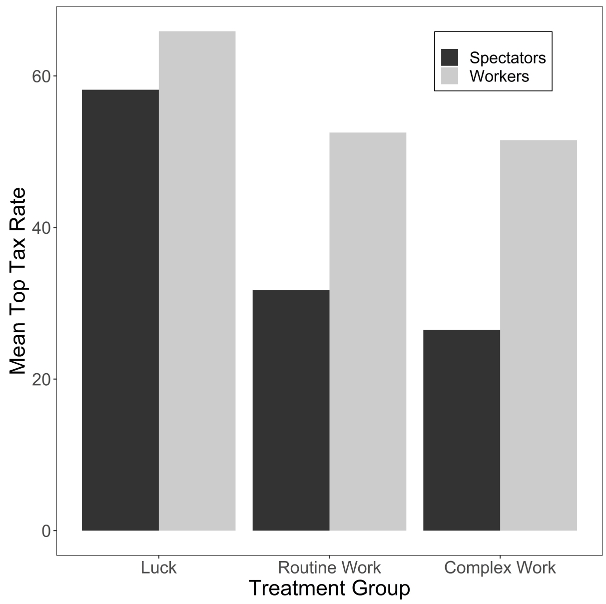
$$TR_i = \beta_0 + \beta_1 R_i + \beta_2 C_i + \epsilon_i \tag{1}$$

$TR_i$ denotes our outcome variables for each respondent i (i.e., tax rate preferences on the highest income earners). $R_i$ is the binary treatment variable for the routine work task and $\beta_1$ is its coefficient. $C_i$ is the binary treatment variable for the complex problems task and $\beta_2$ is its coefficient. For both variables, the indicator takes the value

'1' for the routine/complex work treatment and '0' otherwise. The luck treatment marks the reference category. $\beta_0$ denotes the intercept. $\epsilon_i$ denotes the error term. We estimate Equation 1 and compare the treatment effects for impartial observers and workers separately. Furthermore, we are mainly interested in comparing the effects of different types of work. To investigate whether preferences for redistribution vary significantly between the two types of work, we run additional regression models where we drop the luck treatment group. Here routine work marks the reference category. Standard errors are clustered at the respondent-level.[6]

We run models for impartial spectators and for workers. This allows us to isolate other-regarding preferences by just looking at spectators, who have no material interest at stake in the redistributive decision. In contrast, the results for workers will also be affected by self-interest. By isolating other-regarding preferences through the spectator choices (Cappelen et al., 2013), we can test whether self-interest plays a role in the distributive choices of workers.

Figure 5: Average Tax Rate on Top Earners by Treatment Group



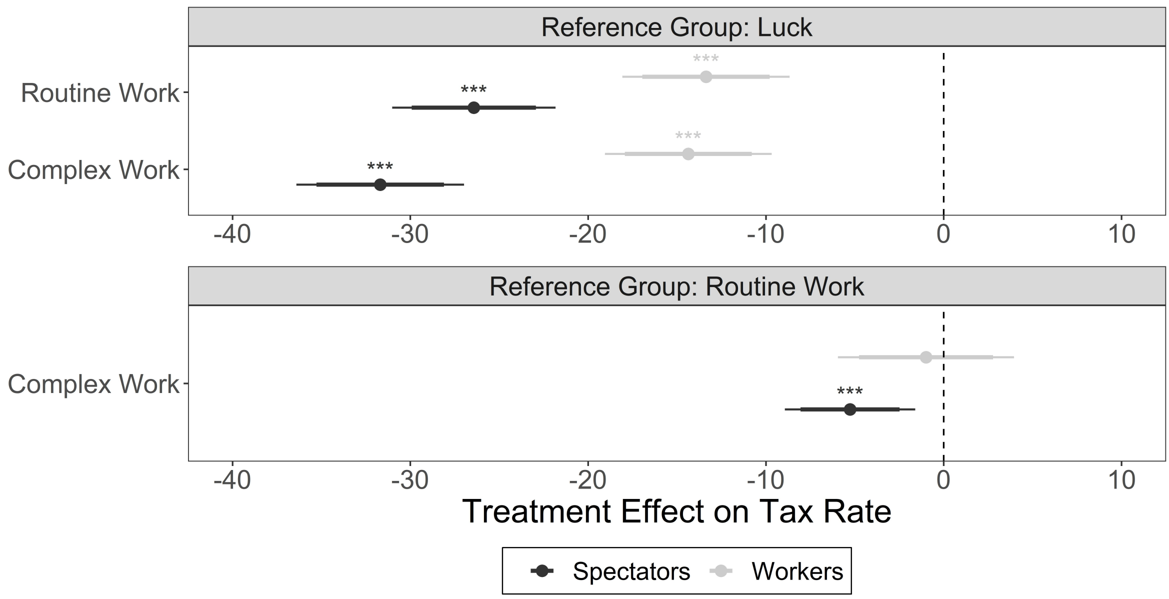

*Note:* The figure shows the average tax rates on the top income earner by treatment condition, separated by spectators and workers.

Before we look at the regression results, let us take a look at the descriptives.

[6] We also check our models by using robust standard errors instead of clustered ones (Figure D1 in the Online Appendix).

Figure 5 shows the average tax rates for the top earner by treatment group. Overall, the tax rate for top earners is higher for workers – who have material interests at stake – compared to impartial spectators. Furthermore, the differences in the average tax rate between treatments are substantially smaller for workers than for spectators. For instance, the preferred tax rate on luck is around 26 percentage points higher than tax rate on routine work for the spectators. For the workers, this difference is only 13 percentage points.

Figure 6: Treatment Effects on Tax Rate on Top Earner




*Note:* The figure shows the treatment effects on the preferred tax rate on the top earner. Results are presented for spectators and for workers. The upper panel uses the luck treatment as a reference category. In the lower panel, the routine work treatment marks the reference group. Results are based on an OLS model with spectator-clustered standard errors. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals. See Table B1 in the Online Appendix for the full models. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure 6 shows the results of the regression models. We start with the other-regarding part of preference formation by looking at the impartial spectators. Both the routine work and the complex work treatments have a strong negative effect on the preferred tax rate on the top earner. Taking the luck treatment as the reference group, the coefficients are highly statistically significant ($p < 0.001$). On average, people prefer a 26.4 percentage points lower tax for the top earners in the routine work group compared to the group where the top earner is determined by luck. For complex work, the preferred tax rate is 31.7 percentage points lower. These results are in line with the large body of work that looks at differences in redistributive preferences when income is earned and when it is obtained by luck. Going beyond this general finding, we can see clear differences when comparing types of work. On average, impartial spectators want a 5.3 percentage points lower tax rate for people who became top earners by performing complex tasks compared to those who became top earners by performing routine tasks. This effect is statistically significant at the 0.001 level.

The findings look different for the workers. Workers have an incentive to maximise their income. First, both work treatments have a substantially weaker impact on the preferred tax rate for the top earner compared to the luck treatment. Compared to the effect size for impartial spectators, the treatment effect is halved. Furthermore, the difference between routine work and complex work drops to 1 percentage point and becomes statistically insignificant. Taken together, these findings indicate that aggregate differences in the preferred tax rate between types of treatment are driven by other-regarding dynamics.

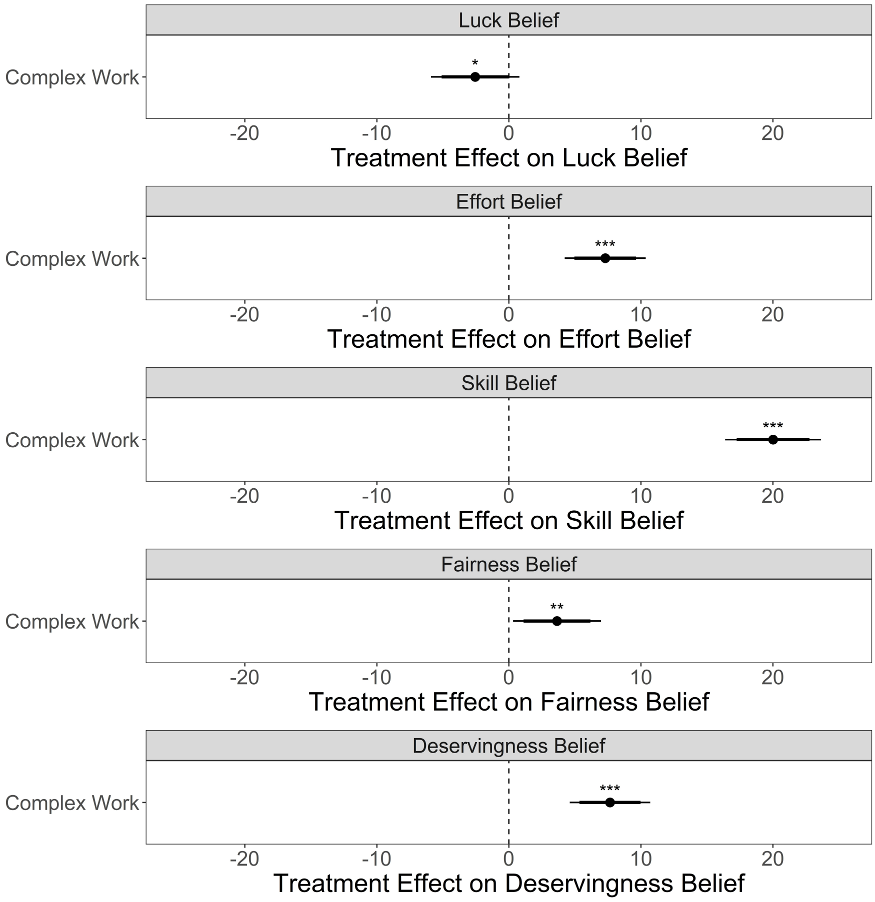
To check whether the results are driven by lack of attention among respondents through the survey, we excluded the quickest 10% of answers for both spectators and workers. The findings are almost identical (see Figure D2 in the Online Appendix). We also drop all those respondents who have not allocated 100 points to the "Luck" option when asked about what matters for receiving the $5 in the luck treatment group. Again, findings hold (see Figure D3 in the Online Appendix). Furthermore, we run interaction models to check whether our findings are driven by subgroup effects (see Table D1 in the Online Appendix). We find no statistically significant variation in the treatment effects when differentiating respondents by characteristics such as gender, age, political affiliation, income, and college degree. Furthermore, we run a robustness check where we control for several socio-economic characteristics (Table D2 in the Online Appendix). Findings hold.

## 4.3 Core Beliefs

To test which other-regarding aspects account for the fact that people want to redistribute less when income differences stem from complex work rather than routine work, we investigate a range of core beliefs. We look at the spectators and investigate the treatment effect on five different types of beliefs. The first three cover luck, effort, and skill. We ask respondents to which extent they think luck/effort/skill is required to perform well on a respective task. In addition, we look at the effect on perceptions of fairness and deservingness. If other-regarding preferences are indeed behind the lower demand for redistribution when people earned their pay-off via complex work, we would expect that people perceive top earners' pay-off as more deserved and fairer. We include two questions asking "To what extent did you think the top earner deserved their $5 bonus in the initial allocation?" and "How fair did you consider the initial allocation of the $5 bonus within the group?" to test this. We ask about all five beliefs after each treatment and respondents could then answer on 11-point range from 0-10 and answers were rescaled to percentage points.

Figure 7 presents the main treatment effects. For all models, we are mainly interested in differences between routine and complex work. Hence, we exclude the luck treatment group. Routine work is the reference category. Respondents believe that slightly less luck is required to do well on the complex work task. The belief that luck is required is 2.6 percentage points lower in the complex work treatment and the effect is statistically significant at the 0.05 level. The results for effort and skill are even more striking. Despite people carrying out both tasks for the exact same amount of time, respondents think that substantially more effort is needed to do well on the complex work task. The effect size is 7.3 percentage points and the finding is statistically highly significant. Furthermore, respondents think that substantially more skill is needed to do well on the complex work task. Compared to the routine work treatment, the complex work treatment increases beliefs that skills are important to do well by 20 percentage points and the effect is highly statistically significant ($p < 0.001$).

Figure 7: Treatment Effects on Core Beliefs




*Note:* The figure shows the treatment effects on perceptions of luck, effort, skill, fairness, and deservingness. In all models, routine-based work is the reference category. Answers were rescaled to percentage points (0-100). Results are based on an OLS model with spectator-clustered standard errors. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals. See Table B2 in the Online Appendix for the full models. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Most importantly, we find that respondents perceive the initial allocation of the bonus as fairer and top earners as more deserving in the complex work treatment than in the routine work treatment. Perceptions of fairness are 3.7 percentage points higher and the effect on perceptions of deservingness is 7.7 percentage points. Both estimates are statistically significant. Together, these findings suggest other-regarding perceptions of fairness and deservingness can help to explain differences in redistributive preferences between types of work. When incomes are the result of complex work, impartial spectators believe inequalities are fairer and top earners are more deserving. This, in turn, can account for lower redistributive demands.

Our additional incentivised belief elicitations outlined in Part F of the Appendix do not show support for any specific rational belief-updating mechanisms. Our results indicate that instead of specific mechanisms, broader beliefs that income differentials arising from complex work are more deserved and fairer than income differentials arising from routine work account for differences in redistributive preferences. Overall, these findings show strong support for our main premise that, with the ICT revolution and the accompanying changes in the nature of labour market tasks, inequalities are seen as fairer and demand for redistribution is dampened.

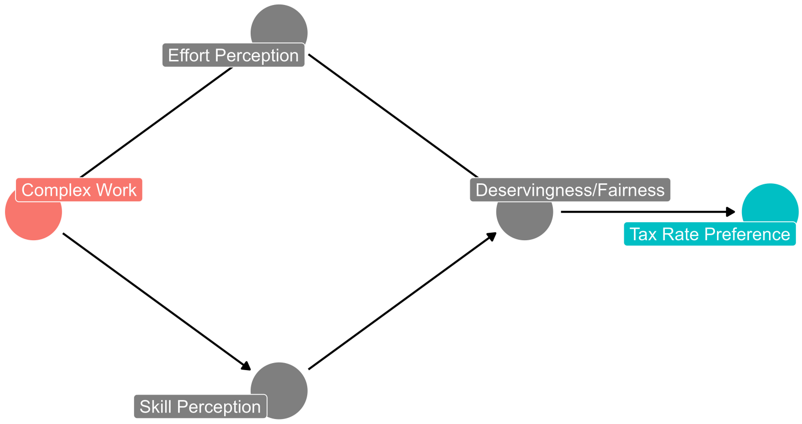
## 4.4 Testing the Causal Chain

So far, we have shown that people prefer lower tax rates for top earners when differences in income stem from complex work. Furthermore, we have shown spectators perceive effort and skill as more important for performing well in the complex work task. Finally, respondents think that the income of top earners who perform complex work is more deserved and that income differences that arise due to complex work are fairer. While we have looked at the effect of the complex work treatments on each of the outcome variables separately in the previous section, we now test the causal chain of our argument. Figure 8 presents an overview of the mechanisms. First, we expect that complex work increases perceptions of skill and effort of top earners which, in turn, means that respondents think top earners' income is more deserved and fair. These higher perceptions of fairness and deservingness should then lead to lower demand for taxing top earners.

We employ causal mediation analysis to test the proposed causal chain (Imai, Keele, Tingley, & Yamamoto, 2011). Causal mediation analysis allows us to test whether the effect of a treatment on an outcome is transmitted via another variable, a so-called mediator. Thus, it allows us to break down the total effect of a treatment into an Average Direct Effect (ADE) and an Average Causal Mediation Effect (ACME).

Our analysis proceeds in two steps. First, we look at how the complex work treatment affects perceived deservingness via perceptions of effort and skill. In other

Figure 8: Causal Chain From Complex Work Treatment to Tax Policy Preferences

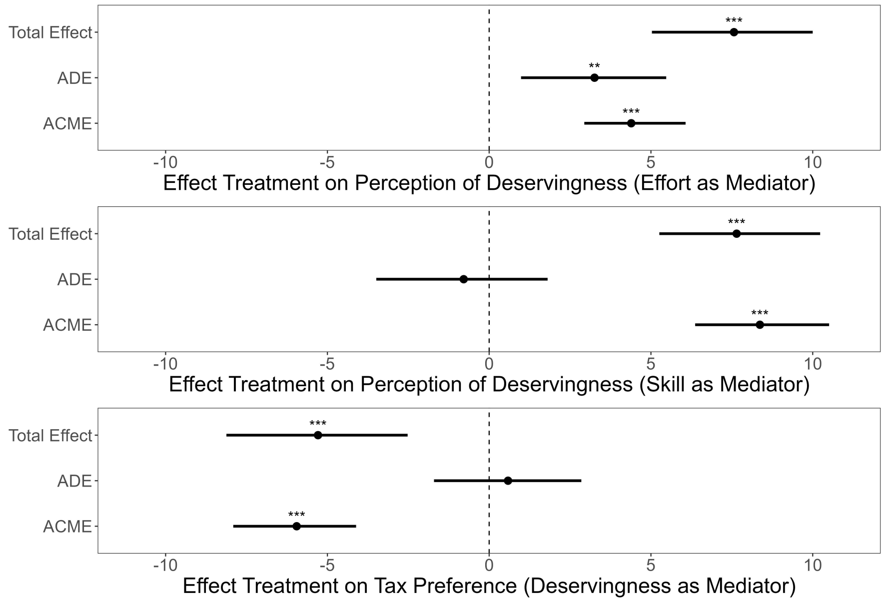



words, we look at effort and skill perceptions as mediators for the treatment effect of complex work on deservingness perceptions. The upper two panels of Figure 9 show the results. When taking either effort or skill as mediators, we can see that a substantial part of the total effect is mediated. When looking at effort, the ACME is around 4.4 percentage points and the ADE is 3.2 percentage points. Both effects are statistically highly significant. In the mediation model that looks at skill perceptions as a mediator, the ACME accounts for all of the total effect, whereas the ADE is statistically insignificant. This leaves us with two main findings. First, the ACME for both effort and skill is positive and statistically significant. Thus, the fact that top earners who performed complex work tasks are seen as more deserving can be explained by the fact that their incomes are perceived to be the result of high levels of both effort and skill. Second, effort and skill perceptions are not mutually exclusive. Skill perceptions, however, seem to be particularly important as a mediator: the ACME is almost twice as large in the model with skill as the mediator than in the one with effort as the mediator.

In a second step, we test whether the effect of complex work on the preferred tax rate for top earners can be explained through its effect on deservingness perceptions. Thus, we now use tax rate preferences as our main outcome variable and deservingness perceptions as the mediator. The bottom panel in Figure 9 shows the results. In line with our theoretical expectations, the ACME accounts for the main treatment effect of complex work on tax rate preferences. In contrast, the ADE is statistically indistinguishable from zero.

In sum, the causal mediation analysis provides support for our main theoretical model. Top incomes stemming from complex work are perceived to result from high levels of effort and skill and, in turn, are seen as more deserving and fair than top incomes that come from routine work.[7] Furthermore, these higher perceptions of deservingness account for the negative effect of complex work on preferences for taxing top earners.

Figure 9: Results Mediation Analysis




*Note:* The figure shows the results of the mediation analyses by plotting the Total Effect, the Average Direct Effect (ADE), and the Average Causal Mediated Effect (ACME). All results were calculated using the Mediation "mediation" R package package (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). In all models, routine-based work is the reference category. Answers were rescaled to percentage points (0-100). Results are based on an OLS model with spectator-clustered standard errors. Bars denote 95% confidence intervals. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[7]We find similar patterns when looking at the fairness item instead of the deservingness, as shown in Part D of the Online Appendix.

# 5 Vignettes Study: Income and Perceived Work Complexity

So far, we have shown that perceptions of work complexity matter for redistributive preferences. In the interactive, online experiment, impartial spectators prefer lower tax rates for top earners who performed more complex tasks as their income is seen as more deserved. However, we do not know whether higher earning individuals are perceived to undertake more complex work. If they are, this would help explain why overall redistributive demands have been so limited in the post-ICT revolution era of rising inequality.

To test whether perceptions of work complexity vary by income, we run a follow-up vignettes study. Respondents each receive four vignettes. The order of the vignettes is randomized. Each vignette describes an (identical) office worker. The only difference between the vignettes is the annual income of the worker. We use four annual income levels: $25,000, $50,000, $100,000, and $500,000. This provides a good spread across the income distribution and includes top earners. The vignettes are worded as follows.

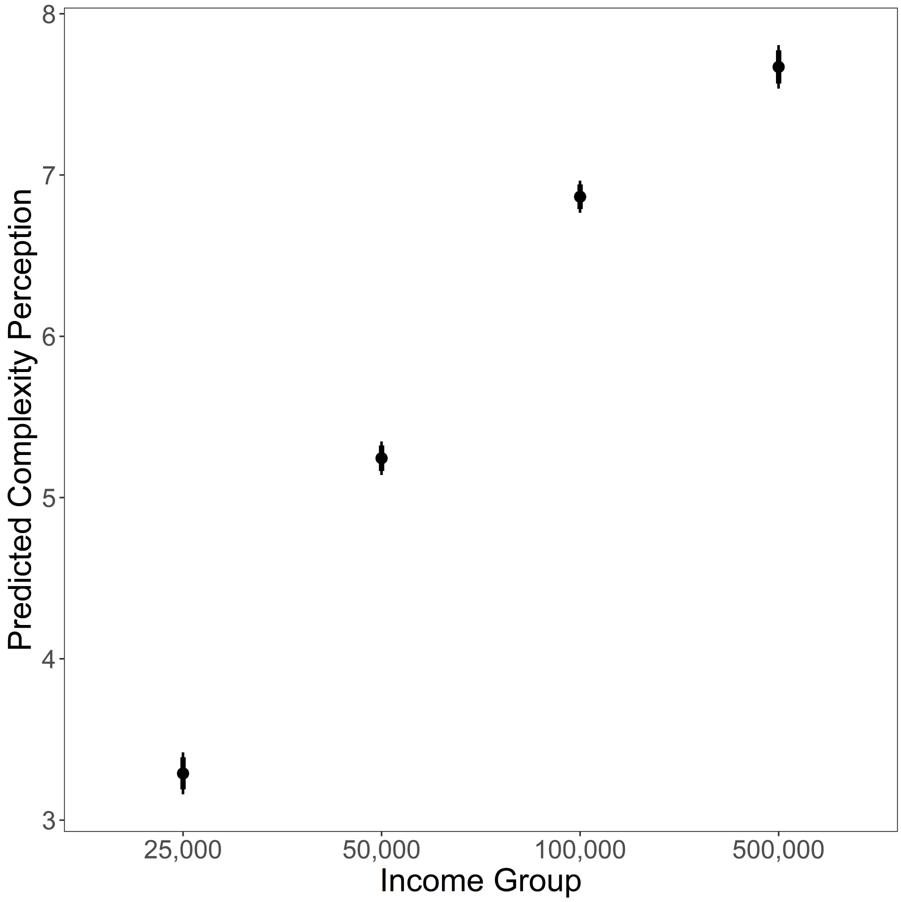
*Consider a person working in an office. They typically work from 9am to 6pm. Their annual income last year was [$25,000/$50,000/$100,000/$500,000].*

Again, we use a within-subjects design. After each vignette, respondents are asked about the perceived complexity of the tasks the individual in the vignette carries out as part of their job. They can answer on an 11-point range from "0 – very routine tasks" to "10 – very complex tasks". We recruited a completely new sample of 2,000 US Americans via Prolific Academic.[8]

Figure 10 presents the results by plotting predicted values of complexity perceptions for each income level. The data show a clear pattern: people perceive that workers with higher incomes perform more complex tasks at work. The differ-

[8]Coding and randomization was implemented via Qualtrics and the vignettes study was preregistered alongside the main interactive online experiment. The fieldwork was conducted between 27th and 28th of January 2023.

Figure 10: Perceived Work Complexity By Income




*Note:* The figure shows the predicted values for perceived work complexity. Predicted values are calculated for each income vignette. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals.

ences between each income group are substantial and highly statistically significant ($p < 0.001$). For the vignette with an income of $25,000, people assign an average work complexity level of around 3.3 points. The perceived complexity rises strongly to 5.2 points for the $50,000 income vignette, 6.9 for $100,000 income vignette, and 7.7 for the vignette with a yearly income of $500,000.[9]

These findings show strong support for the expectation that higher incomes are associated with higher work complexity. This is the case, even though we provide no substantive information about the occupation of the worker. Of course, this finding does not provide evidence that the people perceive the complexity of work undertaken by top earners to have risen in recent decades, as such longitudinal data is not

[9]Table E1 in the Online Appendix presents the treatment effects using the $25,000 income vignette as a reference category.

available to us, but it does suggest that as incomes rise, the perceived complexity of work also rises.

# 6 Conclusion

In this paper, we explore whether redistributive preferences are affected by the complexity of the work that people do. More specifically, we provide new experimental evidence on whether preferences for taxing top earners differ when their incomes have been gained through luck, routine work or complex work. This set up is aiming to mirror the changing nature of tasks in the US labour market in recent decades as a result of the ICT revolution.

We find that impartial spectators, who have no material interest in the redistributive decision, are less willing to redistribute away from top earners, and see their high incomes as more deserved and fairer, when they are the result of complex work. The desired tax rate on top earners is 5.3 percentage points lower in the complex work treatment than the routine work treatment. We do not find similarly significant effects for workers. Taken together, these results highlight the importance of other-regarding preferences (especially fairness and deservingness perceptions) in underpinning the differences in preferred tax rates between the routine and complex work treatments. Our follow-up vignettes study then provides strong evidence that high-earning jobs are widely perceived to be more complex than jobs with lower earnings.

Four contributions stand out. First, we shift attention onto the 'winners' of the ICT revolution, which have been largely ignored in existing literature on technological change and redistributive preferences. Second, we uncover the importance of other-regarding preferences in driving demands for taxing top earners in the knowledge economy. Our results show that there appears to be a widely-held (and acted upon) belief that complex work is more deserving than routine work. Third, we provide new experimental evidence that the increasing complexity of top earners jobs as a result of the ICT revolution matters for redistributive preferences. The desire to tax top earners significantly diminishes when their work is perceived to be more complex. And lastly, our results point to an important new demand-side explanation for why the rise of the knowledge economy has coincided with falling taxes on top incomes, even as it has pushed up income inequality.

There are a number of potentially fruitful directions for future work that come out of our study. For example, it would be important to see the extent to which the results hold outside of the United States, especially in countries with very different fairness and deservingness perceptions such as the Scandinavian countries. Additionally, our experimental evidence could be nicely complemented by observational studies exploring the extent to which the changing task profile of labour markets in advanced economies in recent decades has affected actual tax rates on top incomes.

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# Online Appendix

## Part A: Descriptives

Table A1 presents the balance test between workers and impartial spectators in the main experiment. The dependent variable is a dummy that takes the value '1' for spectators. Overall, there are no major imbalances. The only statistically significant difference can be found for age, with older people being slightly overrepresented in the spectator group. On average, spectators are 1.8 years older than workers. All other socio-economic characteristics do not vary systematically between the two groups.

Table A1: Balance Test

| | Model 1 |
|---|---|
| Male | $-0.0130$ |
| | $(0.0201)$ |
| Income | $-0.0000$ |
| | $(0.0000)$ |
| College Degree | $0.0077$ |
| | $(0.0199)$ |
| Age | $0.0016^{*}$ |
| | $(0.0007)$ |
| Republican (Ref. Dem) | $-0.0114$ |
| | $(0.0389)$ |
| Other (Ref. Dem) | $-0.0438$ |
| | $(0.0310)$ |
| Don't Know (Ref. Dem) | $0.0550$ |
| | $(0.0611)$ |
| Left-Right | $0.0018$ |
| | $(0.0055)$ |
| Unemployed | $0.0595$ |
| | $(0.0367)$ |
| $R^2$ | $0.0067$ |
| Num. obs. | 1949 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

## Part B: Regression Models

Table B1 shows the full regression models for Figure 6 in the main text. Models 1 and 2 show the effect of the treatments on the preferred tax rate for the top earner for spectators. Models 3 and 4 show the effects for workers. In Models 1 and 3, the luck treatment marks the reference category. In Models 2 and 4, we drop the luck treatment observations from the sample and routine word marks the reference category.

Table B1: Regression Results for Treatment Effects on Tax Rate on Top Earner

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| | Spectators | | Workers | |
| Routine Work | $-26.43^{***}$ | | $-13.37^{***}$ | |
| | (1.78) | | (1.82) | |
| Complex Work | $-31.69^{***}$ | $-5.27^{***}$ | $-14.36^{***}$ | $-0.99$ |
| | (1.82) | (1.42) | (1.82) | (1.92) |
| $R^2$ | 0.14 | 0.01 | 0.03 | 0.00 |
| Num. obs. | 1557 | 1038 | 2327 | 1541 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table B2 presents the full regression models for Figure 7. In Models 1, 3, 5, 7, and 9, the luck treatment marks the reference category. In Models 2, 4, 6, 8, and 10, the luck treatment observations are dropped and routine work marks the reference category.

Table B2: Regression Results for Treatment Effects on Core Beliefs

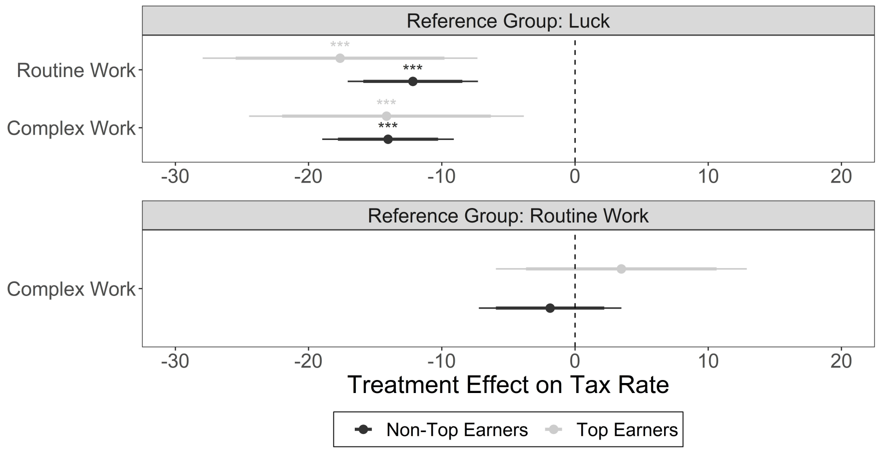
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| | Luck | | Effort | | Skill | | Fairness | | Deservingness | |
| Routine | $-40.36^{***}$ | | $44.44^{***}$ | | $31.88^{***}$ | | $22.35^{***}$ | | $27.98^{***}$ | |
| | (1.99) | | (1.89) | | (1.80) | | (1.75) | | (1.69) | |
| Complex | $-42.91^{***}$ | $-2.55^{*}$ | $51.74^{***}$ | $7.30^{***}$ | $51.90^{***}$ | $20.02^{***}$ | $26.00^{***}$ | $3.65^{**}$ | $35.64^{***}$ | $7.66^{***}$ |
| | (1.94) | (1.29) | (1.87) | (1.19) | (1.75) | (1.40) | (1.86) | (1.29) | (1.69) | (1.18) |
| $R^2$ | 0.29 | 0.00 | 0.39 | 0.02 | 0.35 | 0.13 | 0.10 | 0.00 | 0.20 | 0.02 |
| Num. obs. | 1534 | 1028 | 1508 | 1021 | 1512 | 1025 | 1533 | 1025 | 1496 | 1017 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

## Part C: Differentiating Between Top Earners and Non-Top Earners

The group of workers consist of people who initially get the $5 bonus and those who do not get a bonus. In the main analysis, we have merged these two groups in order to check whether the effect of our treatments varies between these two groups. If our main finding that other-regarding preferences are the main mechanism of the observed treatment effect holds, we would expect to see variation between top earners and non-top earners. More specifically, with growing group size, self-interest motivations should become weaker as chances for direct benefits diminish. Hence, the coefficient of complex work compared to routine-based work should be more similar between the non-top earner group and the spectator group. Figure C1 shows the results when differentiating between top earners and non-top earners. In line with the main findings for workers, the coefficients for both groups are insignificant. However, the effect of complex work for non-top earners becomes slightly negative and converges to the finding for the spectators.

Figure C1: Treatment Effects on Tax Rate For Top Earner, Differentiated By Top Earners and Non-Top Earners

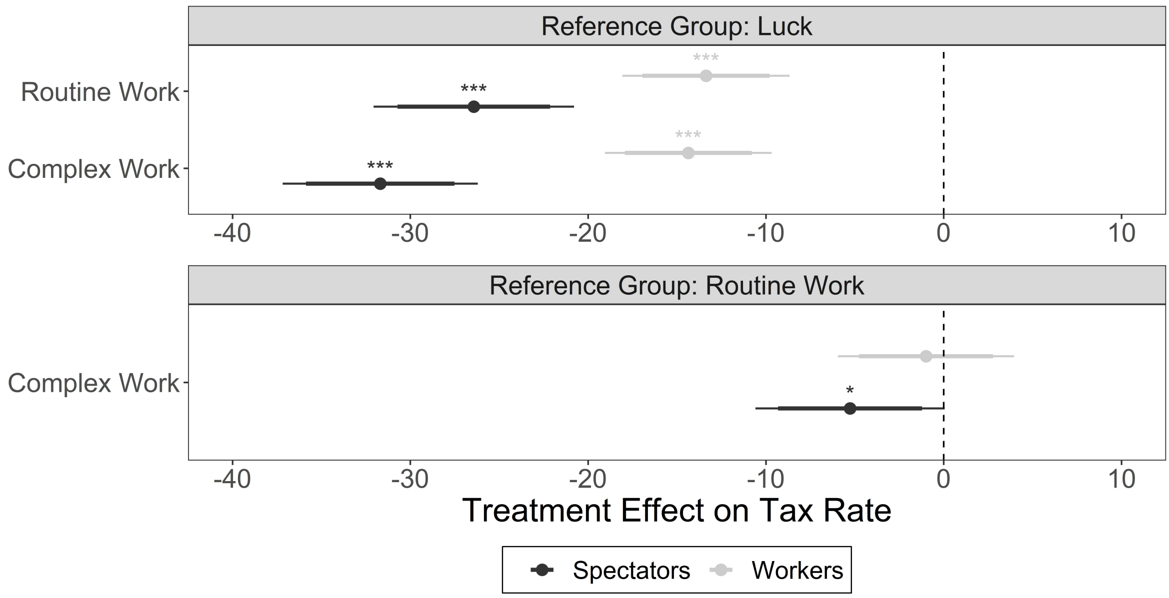



*Note:* The figure shows the treatment effects on the preferred tax rate on the top earner. Results are presented for top earners and for non-top earners. The upper panel uses the luck treatment as a reference category. In the lower panel, the routine work treatment marks the reference group. Results are based on OLS models. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

# Part D: Alternative Models

We check whether our results hold when using standard robust standard errors instead of clustered standard errors. Figure D1 shows the results. Although the significance levels get smaller, the main finding remains robust on the 0.05 level.

Figure D1: Treatment Effects on Tax Rate For Top Earner, Robust Standard Errors



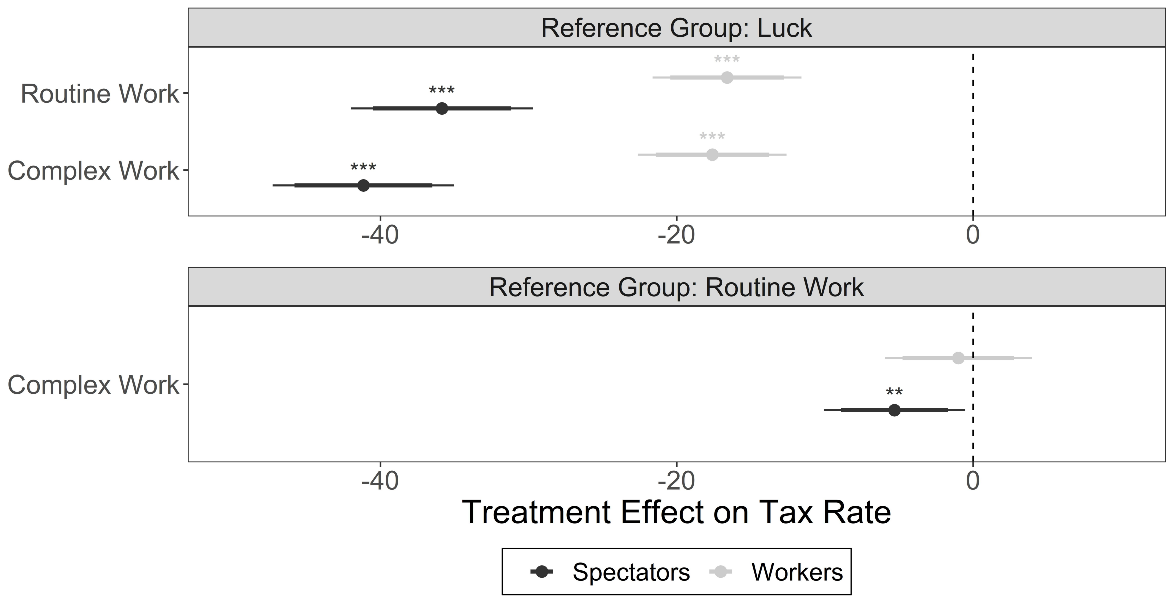

*Note:* The figure shows the treatment effects on the preferred tax rate on the top earner. Results are presented for spectators and for workers. The upper panel uses the luck treatment as a reference category. In the lower panel, the routine work treatment marks the reference group. Results are based on an OLS model with robust standard errors. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

To check that our results are not driven by respondents speeding through the survey, we run additional models where we drop the quickest 10% of respondents (for spectators and workers each). Our main findings hold (Figure D2). Furthermore, we run a subset analysis where we only include those respondents that have assigned 100 points to the "Luck" option when asked why respondents received the $5 in the luck treatment. Again, findings hold (Figure D3).

Figure D2: Treatment Effects on Tax Rate For Top Earner, Quickest 10% Excluded


*Note:* The figure shows the treatment effects on the preferred tax rate on the top earner. Results are presented for spectators and for workers. The upper panel uses the luck treatment as a reference category. In the lower panel, the routine work treatment marks the reference group. Results are based on an OLS model with spectator-clustered standard errors. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure D3: Treatment Effects on Tax Rate For Top Earner, Only 100% Luck Perception




*Note:* The figure shows the treatment effects on the preferred tax rate on the top earner. Results are presented for spectators and for workers. The upper panel uses the luck treatment as a reference category. In the lower panel, the routine work treatment marks the reference group. Results are based on an OLS model with spectator-clustered standard errors. Thick inner bars denote 95% confidence intervals and thin outer bars denote 99% confidence intervals. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

We also check whether our main finding that spectators prefer a lower tax rate for top earners when their income was generated from complex work is driven by subgroup effects. We look at the effect of complex work (routine work marks the reference category) and interact the treatment with variables for gender, age, political affiliation, income, and college degree. None of the interaction effects is statistically significant (Table D1). Hence, our results are unlikely to be driven by specific subgroups.

Table D1: Regression Results for Interaction Effects

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Complex Work | $-6.16^{**}$ | $-1.69$ | $-5.19^{**}$ | $-8.67^{***}$ | $-2.99$ |
| | (1.93) | (4.16) | (1.90) | (2.22) | (1.86) |
| Male | $-3.46$ | | | | |
| | (3.01) | | | | |
| Complex Work * Male | 1.61 | | | | |
| | (2.86) | | | | |
| Age | | 0.06 | | | |
| | | (0.10) | | | |
| Complex Work * Age | | $-0.09$ | | | |
| | | (0.10) | | | |
| Republican | | | $-10.50^{**}$ | | |
| | | | (3.57) | | |
| Complex Work * Republican | | | 2.13 | | |
| | | | (3.74) | | |
| Income | | | | $-0.00^{*}$ | |
| | | | | (0.00) | |
| Complex Work * Income | | | | 0.00 | |
| | | | | (0.00) | |
| College Degree | | | | | 2.74 |
| | | | | | (3.00) |
| Complex Work * College Degree | | | | | $-4.35$ |
| | | | | | (2.81) |
| $R^2$ | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 |
| Num. obs. | 1026 | 1030 | 848 | 1006 | 1038 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table D2 checks whether our results for the group of spectators hold when controlling for a range of additional covariates. It presents the effect of our treatments on the preferred tax rate: In Model 1, the luck treatment marks the reference category. In Model 2, we drop the luck treatment observations from the sample and routine word marks the reference category. Our findings hold.

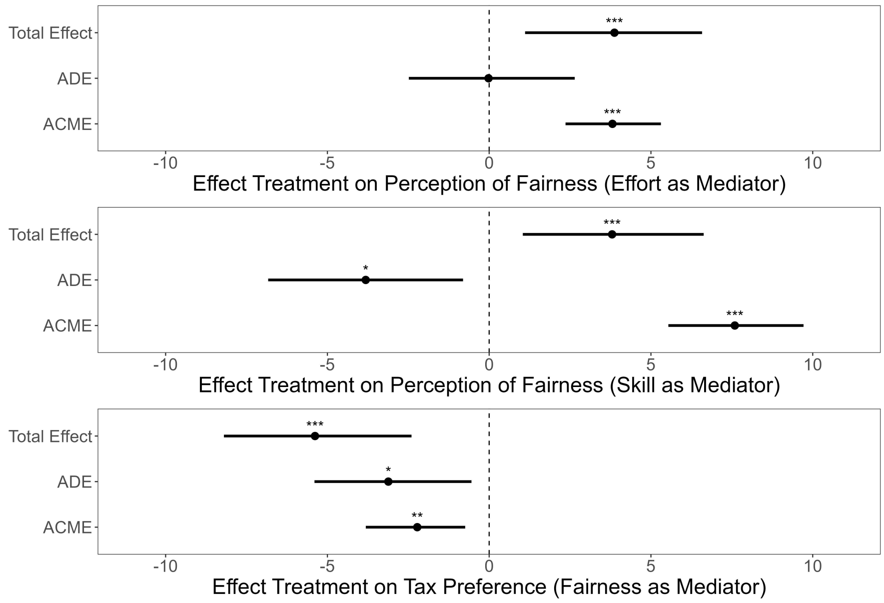
Table D2: Regression Results for Treatment Effects on Tax Rate for Top Earner, Spectators With Covariates

| | Model 1 | Model 2 |
|---|---|---|
| | Spectators | |
| Routine Work | $-26.05^{***}$ | |
| | (2.14) | |
| Complex Work | $-32.05^{***}$ | $-5.99^{**}$ |
| | (2.14) | (2.07) |
| Male | $-0.44$ | $-1.24$ |
| | (1.80) | (2.13) |
| Income | $-0.00$ | $-0.00^{*}$ |
| | (0.00) | (0.00) |
| College Degree | $-1.04$ | $-0.48$ |
| | (1.77) | (2.10) |
| Age | 0.08 | 0.09 |
| | (0.06) | (0.07) |
| Republican (Ref. Dem) | 0.71 | $-1.61$ |
| | (3.52) | (4.17) |
| Other (Ref. Dem) | $-7.18^{*}$ | $-6.05$ |
| | (2.86) | (3.39) |
| Don't Know (Ref. Dem) | $-11.65^{*}$ | $-14.19^{*}$ |
| | (4.95) | (5.86) |
| Left-Right | $-1.79^{***}$ | $-1.57^{**}$ |
| | (0.50) | (0.59) |
| Unemployed | 5.15 | 2.35 |
| | (3.03) | (3.59) |
| $R^2$ | 0.17 | 0.05 |
| Num. obs. | 1488 | 992 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

We also rerun the mediation analysis by looking at fairness perceptions instead of deservingness perceptions. Empirically, the two measurements are strongly correlated ($R$ = 0.75). Figure D4 shows the results. The general findings are similar to the main analysis that looks at deservingness perceptions: Skill and effort perceptions both account for the positive effect of complex work on fairness perceptions, and treatment-induced changes in fairness perceptions moderate a substantial part of the total treatment effect on tax policy preferences.

Figure D4: Results Mediation Analysis




*Note:* The figure shows the results of the mediation analyses by plotting the Total Effect, the Average Direct Effect (ADE), and the Average Causal Mediated Effect (ACME). All results were calculated using the Mediation "mediation" R package package (Tingley et al., 2014). In all models, routine-based work is the reference category. Answers were rescaled to percentage points (0-100). Results are based on an OLS model with spectator-clustered standard errors. Bars denote 95% confidence intervals. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

## Part E: Vignettes Study

Table E1 shows the treatment effects for our follow-up vignettes study, which investigates whether perceived work complexity increases with income. The vignette with a yearly income of $25,000 marks the reference category. We calculate models using clustered standard errors. The findings are in line with the results presented in the main manuscript: Higher income vignettes lead to a higher level of perceived work complexity. The effects are of a significant magnitude, with effect sizes ranging from 1.95 points ($50,000 Income Vignette) to 4.38 points ($500,000 Income Vignette) and are highly statistically significant ($p < 0.001$).

Table E1: Regression Results for Treatment Effects of Income Vignettes on Perceived Work Complexity

| | Model 1 |
|---|---|
| $50,000 Income Vignette | $1.95^{***}$ |
| | (0.07) |
| $100,000 Income Vignette | $3.58^{***}$ |
| | (0.07) |
| $500,000 Income Vignette | $4.38^{***}$ |
| | (0.07) |
| $R^2$ | 0.40 |
| Num. obs. | 8000 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

# Part F: Incentivised Belief Elicitations

## F.1 Design of Belief Elicitations

**Perceived Cognitive Cost:** Subjects are asked whether they would be willing to perform the task (again) within their treatment condition and, if so, what the minimum amount of payment would be they would want to receive for their participation. To put restrictions on subjects' required minimum payments, we inform them that 10 subjects with the lowest suggested amount will be selected to actually complete the task at their proposed rate. Although this introduces a strategic element, it will be held constant across treatments. A higher average required minimum payment in the complex work treatment as opposed to the routine work treatment would suggest that the perceived cognitive cost of the complex problems task is higher. Alternatively, if the required minimum payment in the complex work treatment is lower, it would suggest that the cognitive cost is perceived to be lower. This may be the case because the intrinsic motivation to perform the complex problems task is so high that it outweighs the effect of task difficulty on cognitive cost. Additionally, if one task is perceived to be more engaging than the other, this would reduce the cognitive cost and, in turn, also reduce the required minimum payment in this elicitation. Our measure can therefore provide an estimate of the net cognitive cost of each task, taking all these considerations into account.

**Perceived Agency:** Subjects (within treatment conditions) are asked to provide incentivised estimates of the average performance of workers in two previous studies that differed (only) in the size of the prize given to the best performer. If subjects believe there to be a larger difference in performance for the slider task than for the complex problems task under different prizes, it would suggest that they perceive workers to have more agency over their effort level in the slider task as compared to the complex problems task. While the absolute estimates for these questions will, of course, be affected by their own performance in the task and how intrinsically motivated they believe workers to be, the difference between the two prize scenarios will still capture their perception of agency. If subjects are within +/-5 percentage points of the correct answer for each estimate, they will receive an additional payment of 20 cents.

**Perceived Uniqueness of Skill:** We ask subjects (within treatment conditions) to provide incentivised estimates of the number of workers out of 100 randomly selected ones who were able to perform the task above a certain performance threshold. If subjects are within +/-5 percentage points of the correct answer, they will receive an additional payment of 20 cents. If subjects estimate the number of workers being able to perform very well in the complex problems task to be lower than in the slider task, that would suggest that skills needed for the complex problems task are perceived to be more unique than those needed to perform well in the slider task. The performance threshold is set based on worker performance in the pilot study and corresponds to the number of sliders/complex problems only the top 20% of workers in the pilot were able to complete within 3 minutes.

## F.2 Results of Belief Elicitations

We check three distinct mechanisms that might account for the fact that earnings from complex work are perceived as more deserving and resulting inequalities are seen as fairer. To test for these mechanisms, we compare the results of our three novel belief elicitations outlined above.

**Perceived Cognitive Cost**: More complex tasks might be seen as cognitively more costly. Constantly adapting to more challenging, skill-intensive tasks might be perceived as a higher burden on workers (ceteris paribus). Hence, they might deserve their higher payoffs. To test this mechanism, subjects are asked whether what the minimum amount of payment would be they would want to receive for perform the task again. A higher average required minimum payment in the complex work treatment as opposed to the routine work treatment would suggest that the perceived cognitive cost of the complex problems task is higher. Model 1 in Table F1 shows the results. The effect is positive (around $0.50), but statistically insignificant. Hence, we do not find robust support for the perceived cognitive cost mechanism.

**Perceived Agency**: Agency might play a role. It might, for instance, be the case that individuals have more discretion over the number of tasks that they can fulfil in the complex work treatment than in the routine work treatment. Subjects (within treatment conditions) are asked to provide incentivised estimates of the average performance of workers in two previous studies that differed (only) in the size of the prize given to the best performer. If subjects believe there to be a larger difference in performance for the slider task than for the complex problems task under different prizes, it would suggest that they perceive workers to have more agency over their effort level in the slider task as compared to the complex problems task. We measure the relative difference in percent to make them comparable between treatments. Model 2 in Table F1 shows the results. The findings do not provide support for the perceived agency mechanism. For the complex work group, respondents think that the increase in average performance is slightly higher than for the routine work treatment. However, the finding is statistically indistinguishable from zero.

Table F1: Regression Results for Specific Mechanisms

| | Model 1: Cognitive Costs | Model 2: Agency | Model 3: Uniqueness of Skill |
|---|---|---|---|
| Complex Work | 0.51 | 3.86 | 0.71 |
| | (1.40) | (7.08) | (1.33) |
| $R^2$ | 0.00 | 0.00 | 0.00 |
| Num. obs. | 1036 | 1036 | 1036 |

*Note:* The figure shows the treatment effects on the minimum bonus payment needed to do task again (cognitive costs mechanism), the perception of percentage difference between prize scenarios (agency mechanism), and perception of workers above performance threshold (uniqueness of skill mechanism). In all models, routine work is the reference category. Results are based on an OLS model with spectator-clustered standard errors. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

**Perceived Uniqueness of Skill**: Perceptions of the uniqueness of skills might be crucial. If the ability to perform more complex, skilled tasks is perceived as relatively rare, workers who perform such tasks might be seen as unique and therefore more deserving of a wage premia. Hence, if people perceive the ability to solve complex problems as rare, they might regard a higher reward as justified and fair. We ask subjects (within treatment conditions) to provide incentivised estimates of the number of workers out of 100 randomly selected ones who were able to perform the task above a certain performance threshold. If subjects estimate the number of workers being able to perform very well in the complex problems task to be lower than in the slider task, that would suggest that skills needed for the complex problems task are perceived to be more unique than those needed to perform well in the slider task. Model 3 in Table F1 shows the results. The findings are substantively and statistically insignificant.

# Part G: Experimental Instructions

## G.1 Instructions for Main Experiment

### G.1.1 Worker Instructions -Stage 1

### Treatment Introduction

Thank you for participating in this study. In the following, you will have the opportunity to earn a bonus payment of up to $5. Specifically, you will be asked to complete a task which will take 3 minutes.

After completing this first part of the study, you will be paired with four other participants who completed the same task. The participant with the best performance on the task in the group will be given an initial bonus allocation of $5. You will then be invited to participate in a short follow-up study. The final bonus payments will only be allocated after the follow-up study, so it is important you complete both studies. We will pay out all final bonus payments within 10 days after the follow-up study is completed.

### Control Introduction

Thank you for participating in this study. In the following, you will have a chance to receive a bonus payment of up to $5. There is nothing for you to do in the first part of the study. After completing the first part of the study, you will be paired with four other participants. One of you will be randomly chosen to receive an initial bonus allocation of $5. You will then be invited to participate in a short follow-up study. The final bonus payments will only be allocated after the follow-up study, so it is important you complete both studies. We will pay out all final bonus payments within 10 days after the follow-up study is completed.

## Slider Task

You will now take part in a slider task. You will have to move as many sliders as possible to the number 50. You will have a total of 3 minutes for this task. The participant within your group of five who is able to move the most sliders to 50 will receive an initial bonus allocation of $5.

Please ensure you are ready to begin the task. The 3 min countdown will begin as soon as you proceed to the next page.

## Complex Problems Task

You will now take part in a complex problems task. You will have to correctly answer as many complex problems as possible. You will have a total of 3 minutes for this task. The participant within your group of five who is able to correctly answer the most problems will receive an initial bonus allocation of $5.

There are three types of complex problems you will be asked to solve in random order:

1. Raven's matrices: You will be shown a pattern of figures and asked to identify the missing piece.

2. Multiplication: You will be given a number and asked to identify two numbers that multiply to the given number. For example, if the given number is 18, a possible answer is 2 & 9, as 2x9=18.

3. Anagrams: You will be given 5 letters and asked to form a word that includes all of the 5 given letters. For example, if the letters are eglna, a possible solution is angle.

Please ensure you are ready to begin the task. The 3 minute countdown will begin as soon as you proceed to the next page.

[*Example Problems below.*]

Please move as many sliders as possible to the number 50.

0 10 20 30 40 50 60 70 80 90 100

Please move the slider to 50

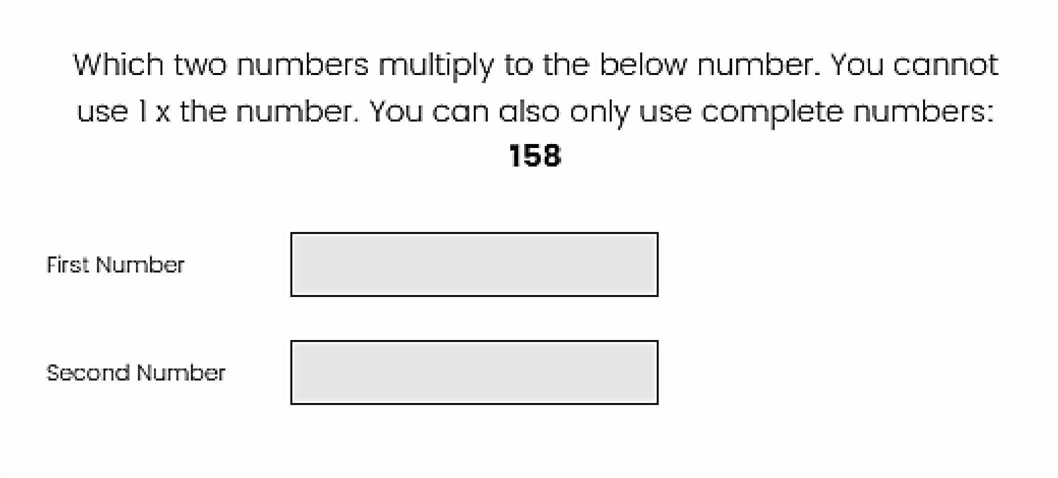
Please move the slider to 50

Please move the slider to 50

Please move the slider to 50

Please move the slider to 50

Please move the slider to 50


Which two numbers multiply to the below number. You cannot use 1 x the number. You can also only use complete numbers:
**158**

First Number

Second Number

## Control End Stage 1

You have now completed the first part of this study.

You will be randomly assigned to a group with four other participants and there will be an initial allocation of the $5 bonus. You will then be invited for a short follow-up study within the next 3 days where you will be asked about your preferences for redistributing the bonus allocation within your group.

We will pay out all final bonus payments within 10 days after this follow-up study. Please note that you will only receive your final bonus payment if you also complete the follow-up study.

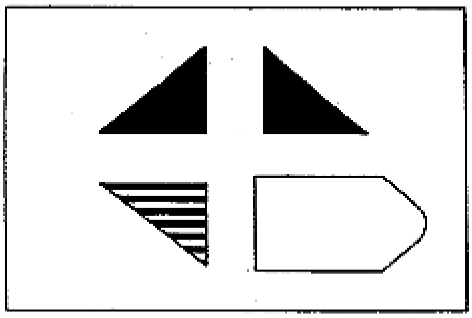
## Treatment End Stage 1

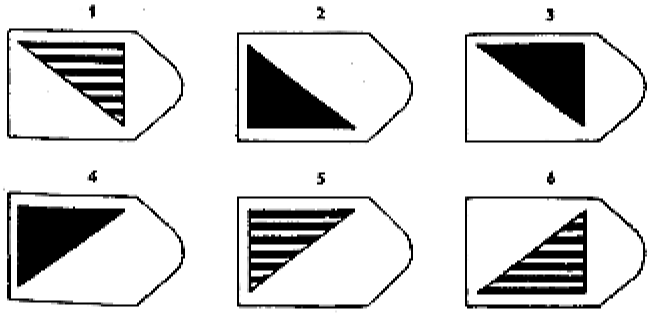
You have now completed the first part of this study.

You will be randomly assigned to a group with four other participants and there will be an initial allocation of the $5 bonus. You will then be invited for a short follow-up study within the next 3 days where you will be asked about your preferences for redistributing the bonus allocation within your group. You will not have to complete any tasks again in this follow up study.

We will pay out all final bonus payments within 10 days after this follow-up study. Please note that you will only receive your final bonus payment if you also complete the follow-up study.

Which of the below options completes the pattern?






| | | |
|---|---|---|
| ○ Option 1 | ○ Option 2 | ○ Option 3 |
| ○ Option 4 | ○ Option 5 | ○ Option 6 |

Find a word that uses all the below letters:

**ehrta**

Your Word

### G.1.2 Worker Instructions - Stage 2

## Complex Problems Task Introduction

Thank you for participating in this follow-up study. In the previous study, you took part in a complex problem task. You were asked to correctly complete as many complex problems as possible within 3 minutes. These complex problems consisted of Raven's matrices, multiplication exercises, and anagrams.

You have now been randomly assigned to a group and the participant who correctly completed the most complex problems within your group has received an initial $5 bonus allocation. On the next screen, you will be asked to decide on the allocation of the $5 bonus within your group. You can redistribute equally among the remaining 4 people in your group any amount of the $5. There is a 50% chance that the decision of an impartial participant who is not part of your group will be implemented and a 50% chance that the decision of someone in your group will be implemented.

We will provide you with information on which member of your group was allocated the initial bonus of $5. You will then have the option to redistribute all or part of the $5. Any indicated amount will be split evenly among everyone else in the group. Please note, that you might be the person who was allocated the $5 initially.

## Slider Task Introduction

Thank you for participating in this follow-up study. In the previous study, you took part in a slider task. You were asked to move as many sliders as possible to the number 50 within 3 minutes.

You have now been randomly assigned to a group and the participant who correctly completed the most sliders within your group has received an initial $5 bonus allocation. On the next screen, you will be asked to decide on the allocation of the $5 bonus within your group. You can redistribute equally among the remaining 4 people in your group any amount of the $5. There is a 50% chance that the decision of an impartial participant who is not part of your group will be implemented and a 50%

chance that the decision of someone in your group will be implemented.
We will provide you with information on which member of your group was allocated the initial bonus of $5. You will then have the option to redistribute all or part of the $5. Any indicated amount will be split evenly among everyone else in the group. Please note, that you might be the person who was allocated the $5 initially.

## Control Introduction

Thank you for participating in this follow-up study.
You have now been randomly assigned to a group and one of you has been randomly chosen to receive an initial $5 bonus allocation. On the next screen, you will be asked to decide on the allocation of the $5 bonus within your group. You can redistribute equally among the remaining 4 people in your group any amount of the $5. There is a 50% chance that the decision of an impartial participant who is not part of your group will be implemented and a 50% chance that the decision of someone in your group will be implemented.
We will provide you with information on which member of your group was allocated the initial bonus of $5. You will then have the option to redistribute all or part of the $5. Any indicated amount will be split evenly among everyone else in the group. Please note, that you might be the person who was allocated the $5 initially.

## Understanding Questions

Before you make your decision, please answer the following questions. Your final payment will not depend on your answers to these questions. However, please answer to the best of your ability as your answers will impact the quality of our research.
**U1:** How many participants are in each group?

- 3
- 4
- 5

- 10

**U2:** If you decide to redistribute $4 of the initial bonus allocation of $5 that one of the participants in your group received, how much will each of the other participants have after your decision?

- $0
- $1
- $4
- $5

**U3:** What is the chance that a redistribution decision made by one of the members of your group will be implemented?

- 25%
- 50%
- 75%
- 100%

Please review the correct answers to the questions below:

**1.** How many participants are in each group?

5

**2.** If you decide to redistribute $4 of the initial bonus allocation of $5 that one of the participants in your group received, how much will each of the other participants have after your decision?

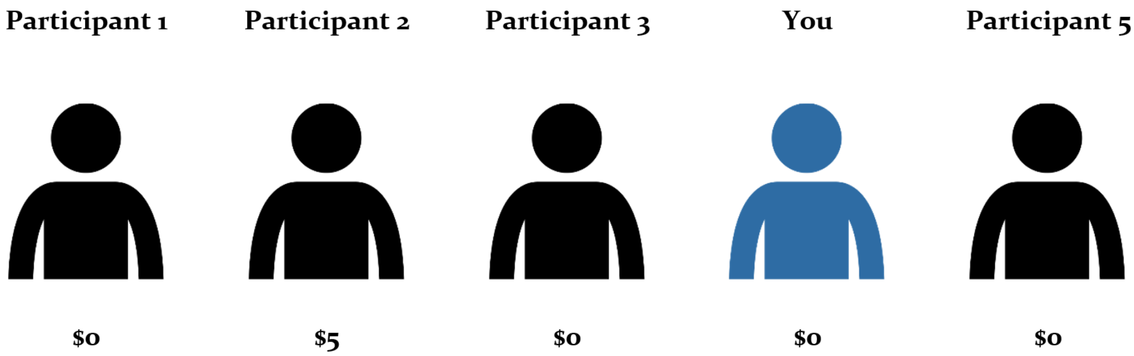
$1

**3.** What is the chance that a redistribution decision made by one of the members of your group will be implemented?

50%

## Decision Screen

Please consider the below information for your group.




You now have the option to redistribute the bonus allocation of *Participant 4*. Participant 4 received the initial $5 bonus allocation because they correctly completed the most sliders/complex problems within your group/was randomly chosen to receive the initial $5 bonus allocation. Please indicate how much of the $5 you wish to redistribute. Any indicated amount will be split evenly among you and the other three participants within the group. If you do not want to redistribute the bonus allocation, you can just enter $0.

**Decision 1:** How much of the $5 do you want to redistribute?
*Amount you want to redistribute (in $):*

## Beliefs and Preferences (treatment text in italics)

**B1:** What was the reason you chose to redistribute the amount you did?

**B2:** How fair did you consider the initial allocation of the $5 bonus within your group?
[*Scale from* 0 *to* 10]

**B3:** To what extent did you think the top earner deserved their $5 bonus in the initial allocation?
[*Scale from* 0 *to* 10]

**B4:** To what extent do you think effort *is required to perform well on the task participants in your group completed*/ was required to receive the initial allocation of the $5 bonus?
[*Scale from* 0 *to* 10]

**B5:** To what extent do you think skill *is required to perform well on the task participants* *in your group completed*/ was required to receive the initial allocation of the $5 bonus? [*Scale from* 0 *to* 10]

**B6:** To what extent do you think luck *is required to perform well on the task participants in your group completed*/ was required to receive the initial allocation of the $5 bonus? [*Scale from* 0 *to* 10]

**B7:** Why do you think *some perform well on the task participants in your group completed*/one participant received the initial allocation of the $5 bonus? Please allocate a total of 100 points across the below four options. Please ensure that the more points you allocate to an option, the more important you consider it to *be able to perform well on the task*/receive the initial allocation of the $5 bonus. Please allocate all 100 points before proceeding.

- Inherited Intelligence
- Education
- Luck
- Effort

**M1:** *What would be the minimum bonus payment you would need to receive to participate in a follow-up study where you complete the same task again for 3mins? You will not be informed of your performance on the task. We will select the 10 participants who suggest the lowest amount to participate in the follow-up study and they will receive their stated minimum bonus payment in return.*

**M2a:** *We previously asked 100 participants to also complete the same task that you completed for 3mins. There were a total of 100 sliders/ 30 complex problems that could be attempted in this study. The participant with the highest performance received a prize of $10. How many of those 100 possible sliders/ 30 possible complex problems do you think participants in this study completed on average? If your guess lies within +/- 5 percentage points of the correct answer you will receive an additional bonus payment of 20ct.*

**M2b:** *In another study, we again asked 100 participants to also complete the same task that you completed for 3mins. There were a total of 100 sliders/ 30 complex problems that could*

*be attempted in this study. The participant with the highest performance however received a prize of $30. How many of those 100 possible sliders/ 30 possible complex problems do you think participants in this study completed on average? If your guess lies within +/- 5 percentage points of the correct answer you will receive an additional bonus payment of 20ct.*
**M3:** *Consider again the task you completed at the beginning of this study. We randomly selected 100 participants who also completed this task as part of our study. How many of these 100 participants do you believe were able to correctly complete more than 12 pages of sliders/ 12 complex problems within the 3mins? If your guess lies within +/- 5 percentage points of the correct answer you will receive an additional bonus payment of 20ct.*

### G.1.3 Spectator Instructions

### General Introduction

Thank you for participating in this study.
In the following, you will be asked to decide on an allocation of money between groups of five participants three times. There is a 50% chance that one of your three allocation decisions will be implemented and will decide the actual payoffs of those five participants. Please consider each of your three decisions carefully as we will not tell you which of your decisions is the one that might be implemented.

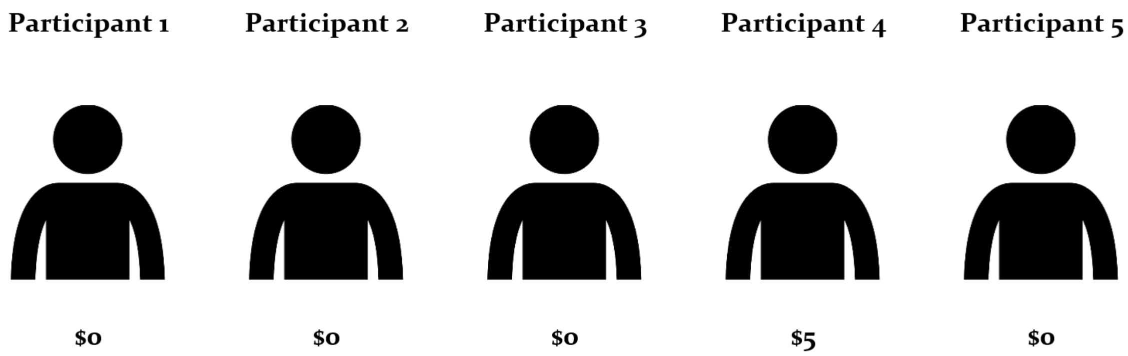
### Introduction Slider Task Decision

The five participants in the group had 3 minutes to move as many sliders as possible to the number 50. The participant who correctly completed the most sliders in the group received an initial bonus allocation of $5, while the others received nothing. To give you a better understanding of the task, you can now try it yourself for 1 min.

*[Slider Task]*

In the following, you will be shown a scenario similar to the one below. Each of

the five participants in the group completed the slider task. The participant who correctly completed the most sliders in the group received an initial bonus allocation of $5, while the others received nothing.
You are given information on the current bonus allocations of the five participants in the group. Before we pay out these bonus payments, however, you have the opportunity to redistribute part or all of the $5 within the group. Any indicated amount will be split evenly among the other four participants within the group.




## Introduction Complex Problems Task Decision

The five participants in the group had 3 minutes to answer as many complex problems as possible. The participant who answered the most complex problems correctly in the group received an initial bonus allocation of $5, while the others received nothing. To give you a better understanding of the task, you can now try it yourself for 1 min. There are three types of complex problems you will be asked to solve in random order:

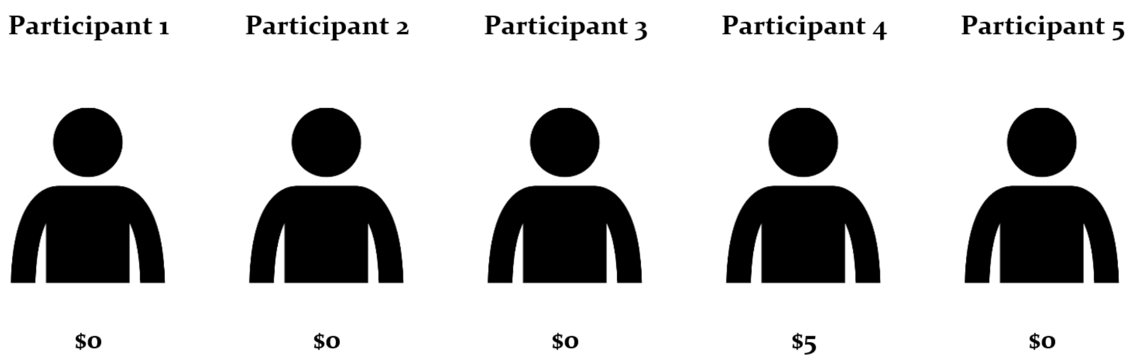
1. Raven's matrices: You will be shown a pattern of figures and asked to identify the missing piece.

2. Multiplication: You will be given a number and asked to identify two numbers that multiply to the given number. For example, if the given number is 18, a possible answer is 2 & 9, as 2x9=18.

3. Anagrams: You will be given 5 letters and asked to form a word that includes all of the 5 given letters. For example, if the letters are eglna, a possible solution is angle.

*[Complex Problems Task]*

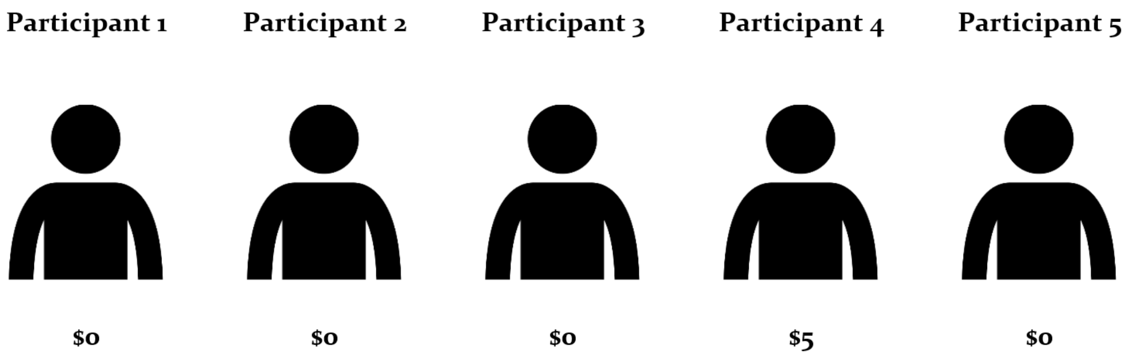
In the following, you will be shown a scenario similar to the one below. Each of the five participants in the group completed the complex problems task. The participant who answered the most complex problems correctly in the group received an initial bonus allocation of $5, while the others received nothing.
You are given information on the current bonus allocations of the five participants in the group. Before we pay out these bonus payments, however, you have the opportunity to redistribute part or all of the $5 within the group. Any indicated amount will be split evenly among the other four participants within the group.




## Introduction Control Decision

You will be shown a scenario similar to the one below. One of the five participants in the group was randomly chosen to receive an initial bonus allocation of $5, while the others received nothing.
You are given information on the current bonus allocations of the five participants in the group. Before we pay out these bonus payments, however, you have the opportunity to redistribute part or all of the $5 within the group. Any indicated amount will

be split evenly among the other four participants within the group.




## Understanding Questions

Before you make your first decision, please answer the following questions. Your final payment will not depend on your answers to these questions. However, please answer to the best of your ability as your answers will impact the quality of our research.

**U1:** What is the chance that one of your allocation decisions will be implemented and decide the bonus payments for the group?

- 10%
- 25%
- 50%
- 100%

**U2:** How many participants are in each group?

- 3
- 4
- 5
- 10

**U3:** If you decide to redistribute 4$oftheinitialbonusallocationof$5 that one of the participants in the group received, how much will each of the other participants have after your decision?

- $0
- $1
- $4
- $5

Please review the correct answers to the questions below:

**1.** What is the chance that one of your allocation decisions will be implemented and decide the bonus payments for the group?

50%

**2.** How many participants are in each group?

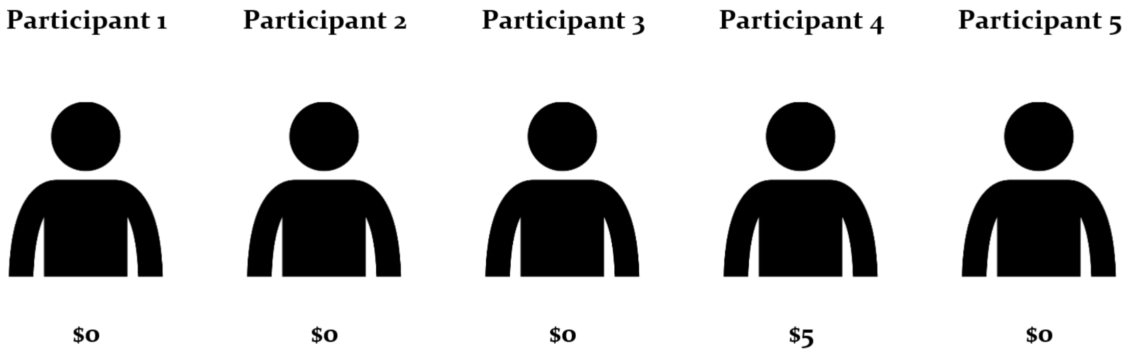
5

**3.** If you decide to redistribute $4 of the initial bonus allocation of $5 that one of the participants in the group received, how much will each of the other participants have after your decision?

$1

## Decision Screens

Please carefully consider the below scenario.




You now have the option to redistribute the bonus allocation of *Participant 4*. Participant 4 received the initial $5 bonus allocation because they correctly completed the most sliders/complex problems within the group/was randomly chosen to receive the initial $5 bonus allocation. Please indicate how much of the $5 you wish to redistribute. Any indicated amount will be split evenly among the other four participants within the group. If you do not want to redistribute the bonus allocation, you can just enter $0.

**Decision 1:** How much of the $5 do you want to redistribute?
*Amount you want to redistribute (in $):*

## Beliefs and Preferences (treatment text in italics)

**B1:** What was the reason you chose to redistribute the amount you did?
**B2:** How fair did you consider the initial allocation of the $5 bonus within the group?
[*Scale from* 0 *to* 10]
**B3:** To what extent did you think the top earner deserved their $5 bonus in the initial allocation?
[*Scale from* 0 *to* 10]

**B4:** To what extent do you think effort *is required to perform well on the task participants in this group completed*/ was required to receive the initial allocation of the $5 bonus? [*Scale from* 0 *to* 10]

**B5:** To what extent do you think skill *is required to perform well on the task participants in this group completed*/ was required to receive the initial allocation of the $5 bonus? [*Scale from* 0 *to* 10]

**B6:** To what extent do you think luck *is required to perform well on the task participants in this group completed*/ was required to receive the initial allocation of the $5 bonus? [*Scale from* 0 *to* 10]

**B7:** Why do you think *some perform well on the task participants in this group completed*/one participant received the initial allocation of the $5 bonus? Please allocate a total of 100 points across the below four options. Please ensure that the more points you allocate to an option, the more important you consider it to *be able to perform well on the task*/receive the initial allocation of the $5 bonus. Please allocate all 100 points before proceeding.

- Inherited Intelligence
- Education
- Luck
- Effort

**M1:** *What would be the minimum bonus payment you would need to receive to participate in a follow-up study where you complete the same task again for 3mins? You will not be informed of your performance on the task. We will select the 10 participants who suggest the lowest amount to participate in the follow-up study and they will receive their stated minimum bonus payment in return.*

**M2a:** *We previously asked 100 participants to also complete the same task that you completed for 3mins. There were a total of 100 sliders/ 30 complex problems that could be attempted in this study. The participant with the highest performance received a prize of $10. How many of those 100 possible sliders/ 30 possible complex problems do you think participants in this* *study completed on average? If your guess lies within +/- 5 percentage points of the correct answer you will receive an additional bonus payment of 20ct.*

**M2b:** *In another study, we again asked 100 participants to also complete the same task that you completed for 3mins. There were a total of 100 sliders/ 30 complex problems that could be attempted in this study. The participant with the highest performance however received a prize of $30. How many of those 100 possible sliders/ 30 possible complex problems do you think participants in this study completed on average? If your guess lies within +/- 5 percentage points of the correct answer you will receive an additional bonus payment of 20ct.*

**M3:** *Consider again the task you completed at the beginning of this study. We randomly selected 100 participants who also completed this task as part of our study. How many of these 100 participants do you believe were able to correctly complete more than 12 pages of sliders/ 12 complex problems within the 3mins? If your guess lies within +/- 5 percentage points of the correct answer you will receive an additional bonus payment of 20ct.*

## Second Decision Introduction

You have now completed your first allocation decision.
Please remember that there is a 50% chance that one of your three allocation decisions will be implemented and will decide the actual payoffs of the group of participants.
Please click on the arrow below to proceed to your second decision.

## Third Decision Introduction

You have now completed your second allocation decision.
Please remember that there is a 50% chance that one of your three allocation decisions will be implemented and will decide the actual payoffs of the group of participants.
Please click on the arrow below to proceed to your third and final decision.

### G.1.4 Demographics (Workers and Spectators)

In this final part of the study, we will ask you a number of questions about yourself. Please read the questions carefully and answer honestly. This part should take only 2-3 minutes.

**D1: Age.** How old are you?

**D2: Gender.** What is your gender?

- Female
- Male
- Other
- Prefer not to say

**D3: Ethnicity.** To which of these groups do you consider you belong? You can choose more than one group.

- American Indian or Alaska Native
- Asian
- Black or African-American
- Native Hawaiian or other Pacific Islander
- Spanish, Hispanic or Latino
- White
- Other group
- Prefer not to answer

**D4: Education.** Which category best describes your highest level of education?

- Primary education or less
- Some high school

- High school degree/GED
- Some college
- 2-year college degree
- 4-year college degree
- Master's degree
- Doctoral degree
- Professional degree (JD, MD, MBA)
- Prefer not to answer

**D5: Household Income.** What is your total (annual) household income before tax?

- Under $10,000
- $10,000 - $20,000
- $20,001 - $30,000
- $30,001 - $40,000
- $40,001 - $50,000
- $50,001 - $60,000
- $60,001 - $80,000
- $80,001 - $100,000
- $100,001 - $150,000
- $150,001 - $200,000
- $200,001 - $350,000
- $350,001 - $500,000

- Above \$500,000
- Don't know
- Prefer not to answer

**D6: Employment Status.** What is your current employment status?

- Full-time employee
- Part-time employee
- Self-employed or small business owner
- Medium or large business owner
- Unemployed and looking for work
- Student
- Not currently working and not looking for work (e.g. full-time parent)
- Retiree
- Prefer not to answer

**D7: Economics.** Have you ever taken a module on economics or a related subject area at university?

- Yes
- No
- I have never attended higher education

**D8: Political Orientation.** In politics people sometimes talk of left and right. Where would you place yourself on the following scale?
*[Scale from 0 (Left) to 10 (Right).]*

**D9: Party Affiliation.** Which party do you feel closest to?

- Democratic party
- Republican party
- Other
- Don't know

**D10: 2020 Vote.** Who did you vote for in the recent 2020 Presidential Election?

- Joe Biden
- Donald Trump
- Other candidate
- Didn't vote
- Don't remember
- Prefer not to say

**D11: Risk Preference.** Please tell us, in general, how willing or unwilling you are to take risks. Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and a 10 means you are "very willing to take risks". You can also use any numbers between 0 and 10 to indicate where you fall on the scale.

**D12: Ambiguity Aversion.** Please respond to the following statements by indicating the extent to which you agree or disagree with them on a scale from 1 (I strongly agree) to 7 (I strongly disagree).

- There is a right way and a wrong way to do almost everything
- Practically every problem has a solution
- I feel relieved when an ambiguous situation suddenly becomes clear
- I find it hard to make a choice when the outcome is uncertain

**D13: Feedback.** Do you have any feedback or impressions regarding this study?

## G.2 Vignettes Study Instructions

### Introduction

Thank you for participating in this study.

In the following, you will be given four scenarios in which individuals earn different incomes. You will then be asked about the type of work you believe these individuals do. Please consider each scenario individually and keep in mind that we are interested in your personal opinion.

Your answers will be used solely for academic research. The study is being carried out by non-partisan academic researchers seeking to advance our knowledge of society. It is important for the research that you answer as accurately as you can, so please read each of the statements and questions carefully.

### Vignettes

**V1. $25,000 income.** Consider a person working in an office. They typically work from 9am to 6pm. Their annual income last year was $25,000.

**V2. $50,000 income.** Consider a person working in an office. They typically work from 9am to 6pm. Their annual income last year was $50,000.

**V3. $100,000 income.** Consider a person working in an office. They typically work from 9am to 6pm. Their annual income last year was $100,000.

**V4. $500,000 income.** Consider a person working in an office. They typically work from 9am to 6pm. Their annual income last year was $500,000.

### Beliefs and Preferences

**B1.** How complex do you believe the tasks this person completes at work are?
[$Scale\ from\ 0\ -\ very\ routine\ tasks\ to\ 10\ -\ very\ complex\ tasks.$]

## Reasoning

**R1.** What was your rationale for your answers to the previous questions?