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The ICT revolution and preferences for taxing top earners

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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 3000 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.

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KEYWORDS ICT revolution; labour markets; redistributive preferences; tax policy

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-

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routine cognitive tasks that are complementary to new technologies have significantly expanded (Acemoglu & Autor, 2011; Autor et al., 2003; Caines et al., 2017; Goos et al., 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, 2008), and has been clearly linked to both the rise in the college wage premia (Autor, 2014; Autor et al., 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 & 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 et al., 2021; Frey et al., 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, et al., 2022) and to redistribute income from the rich to the poor (Busemeyer & Sahm, 2022; 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, et al., 2022; Schöll & Kurer, 2024), 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 et al., 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 & 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 3000 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 et al., 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 & 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 et al., 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. The second section reviews the relevant literature and sets out our theory. The third section describes our experimental design. The fourth section presents the main results of our experiment, as well as an exploration of the mechanisms at work. The fifth section then presents the results of our follow-up vignettes study. Lastly, we provide some concluding remarks in the sixth section.

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.

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, 2022; 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 et al., 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 et al., 2022; Jeffrey, 2021). Furthermore, following the general rise of studies looking at trade-offs between different policies (Bremer & Bürgisser, 2023; Häusermann et al., 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, et al., 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, 2008). 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 et al., 2018).

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, 2008; 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 et al., 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 et al., 2014). Furthermore, appetite for top income taxation is higher when people believe that the rich were treated preferentially by the state (Scheve & Stasavage, 2016, 2023).

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 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).

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, 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 nonroutine 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 towards 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 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 per cent chance that the decision of one of three impartial spectators will be implemented[4] and a 50 per cent chance that the decision of one of the five workers will be implemented. This setup, in which spectators and workers each face a 50 per cent 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 treatment 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.

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

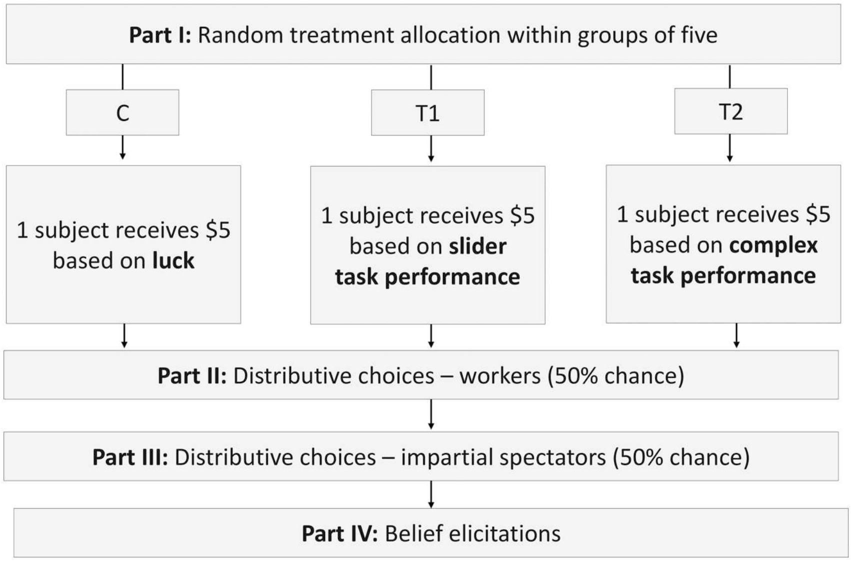

Figure 1. Experimental design.

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).

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.

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 per cent chance the decision of one of the five workers will be implemented and that worker is chosen at random, there is a 10 per cent chance an individual worker's decision will be implemented. The left

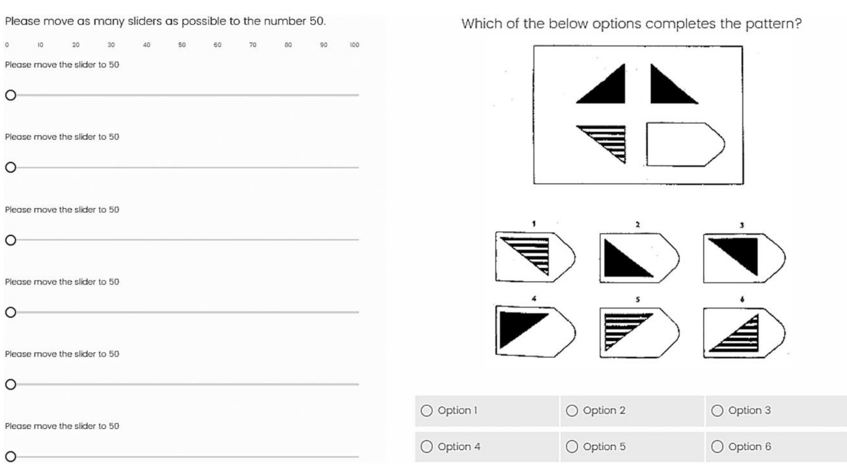

Figure 2. Example worker screens.

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

panel in Figure 3 illustrates an example decision scenario for a worker who is not herself a top earner in the complex work condition.

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 per cent chance the decision of one of the three spectators will be implemented. As that spectator is chosen at random, there is a 17 per cent chance an individual spectator's decision will be implemented. Spectators receive no information on the preferences expressed by the workers in

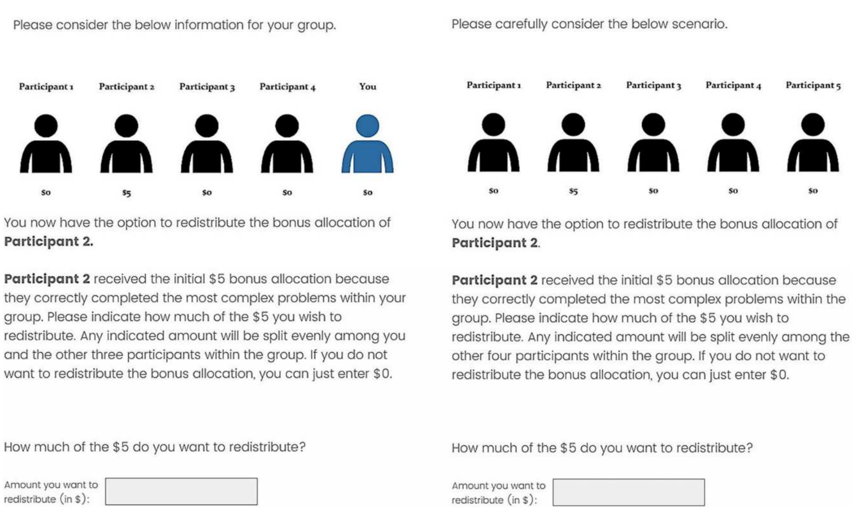

Figure 3. Example distribution screens.

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

part II. The right panel in Figure 3 illustrates an example decision scenario for a spectator in the complex work condition.

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 2366 workers.[5] Our experimental design and the following analysis were pre-registered via the American Economic Association's registry for Randomised Controlled Trials with the reference ID AEARCTR-0009719. The average time subjects took to complete the experiment was 12 min for workers and 18 min for spectators. The average earnings of workers was \$2.79 and the average earnings of spectators was \$2.59.

Results

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,

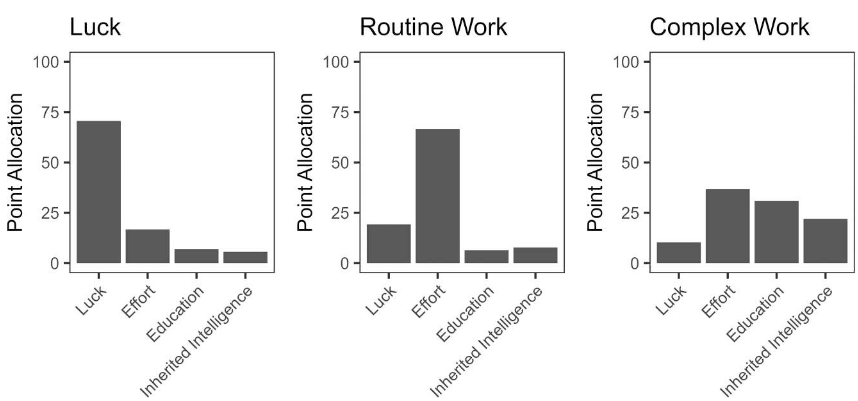

Figure 4. Perceptions of what matters for performance across treatments.

Note: Point allocation based on the 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.'

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

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 per cent for top earners, and \$0 resulting in a tax rate of 0 per cent. 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 β_1 is its coefficient. C_i is the binary treatment variable for the complex problems task and β_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. β_0 denotes the intercept. ϵ_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.

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

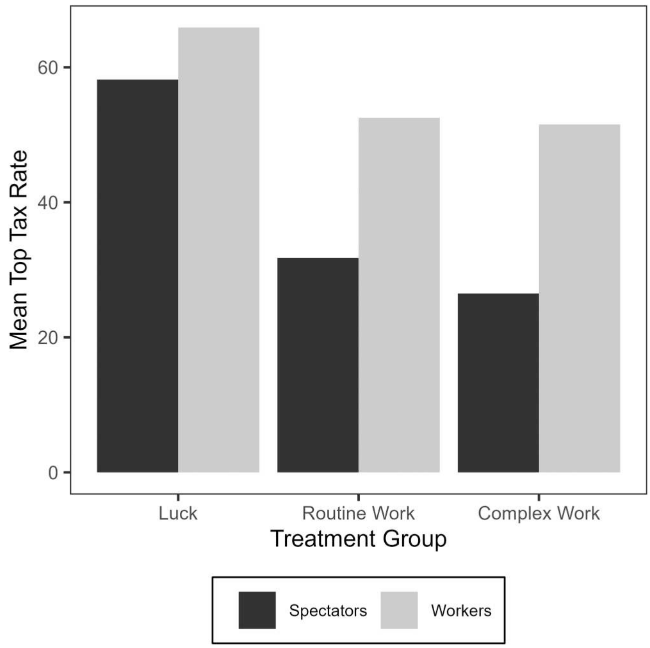

Figure 5. Average tax rate on top earners by treatment group.

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

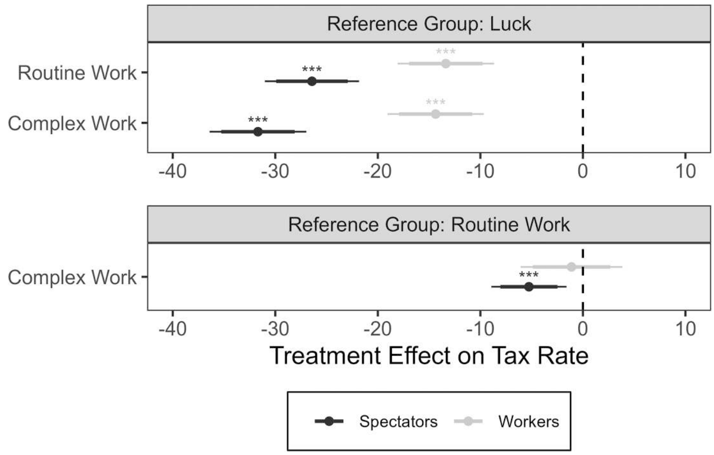

Figure 6. Treatment effects on tax rate on top earner.

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. $***p < 0.001$, $**p < 0.01$, $*p < 0.05$.

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 per cent 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.

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

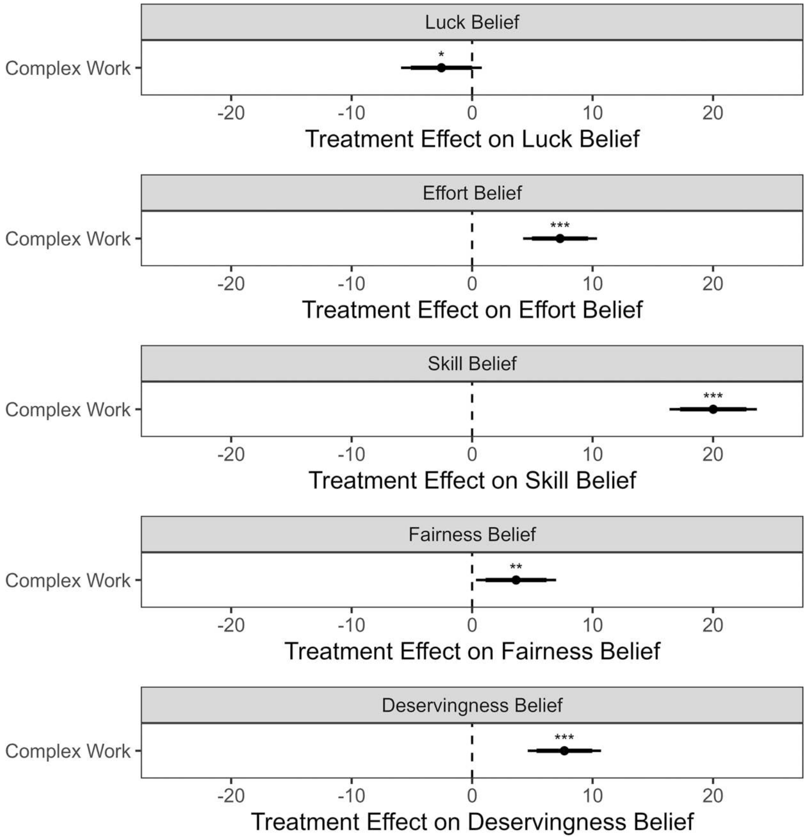

Figure 7. Treatment effects on core beliefs.

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. $***p < 0.001$, $**p < 0.01$, $*p < 0.05$.

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 ($p < 0.001$).

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.

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 fairer. 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 et al., 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 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

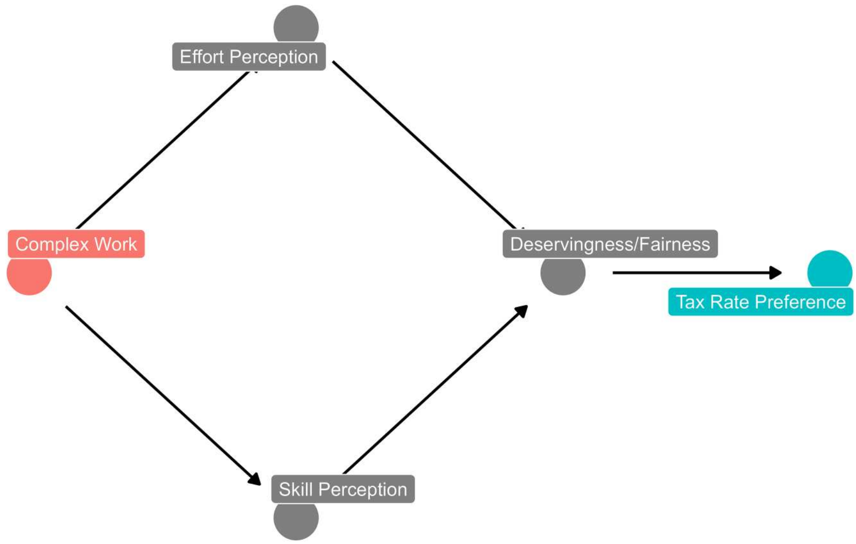

Figure 8. Causal chain from complex work treatment to tax policy preferences.

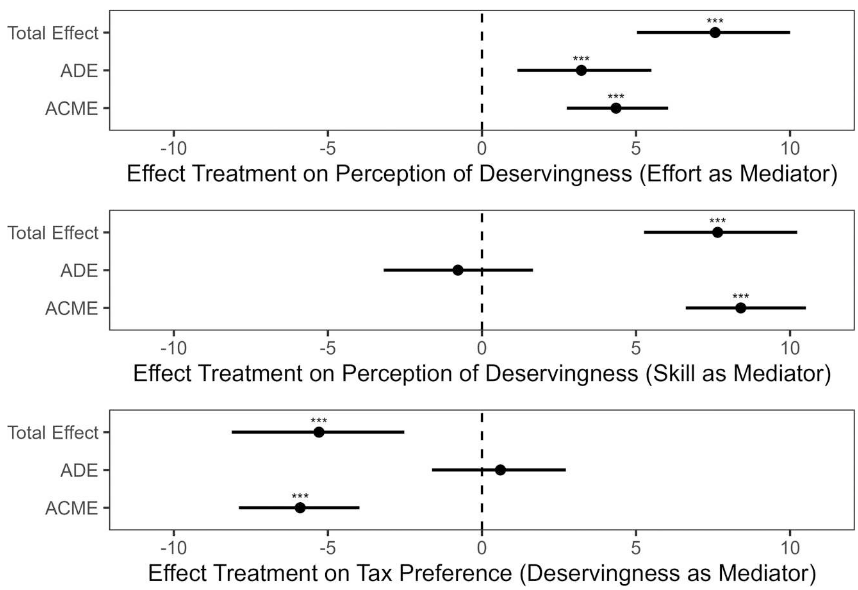

Figure 9. Results mediation analysis.

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' R 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. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

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 fairer 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.

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 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 randomised. 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 2000 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 differences 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

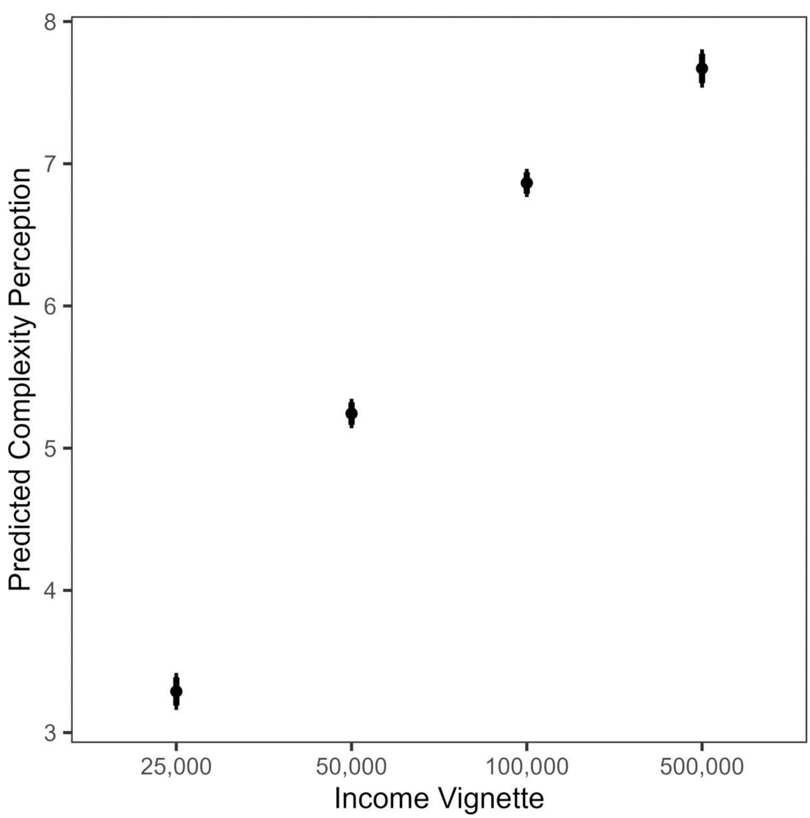

Figure 10. Perceived work complexity by income.

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.

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

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.

Notes

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 & 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.
2. The work by Scheve and Stasavage (2016) is a notable exception as they show how warfare can lead to changing fairness perceptions.
3. Autor et al. (2003) split non-routine cognitive tasks into non-routine analytical tasks and nonroutine 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.
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 per cent chance of implementation.
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.
6. We also check our models by using robust standard errors instead of clustered ones (Figure D1 in the Online Appendix).

7. We find similar patterns when looking at the fairness item instead of deservingness, as shown in Part D of the Online Appendix.
8. Coding and randomization were 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.
9. Table E1 in the Online Appendix presents the treatment effects using the $25,000 income vignette as a reference category.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature*, *40*(1), 7–72. https://doi.org/10.1257/0022051026976

Acemoglu, D., & Autor, D. (2011). Chapter 12 - skills, tasks and technologies: Implications for employment and earnings. In D. Card, & O. Ashenfelter (Eds.), *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Ackert, L. F., Martinez-Vazquez, J., & Rider, M. (2007). Social preferences and tax policy design: Some experimental evidence. *Economic Inquiry*, *45*(3), 487–501. https://doi.org/10.1111/j.1465-7295.2007.00048.x

Alesina, A., & Angeletos, G.-M. (2005). Fairness and redistribution. *The American Economic Review*, *95*(4), 960–980. https://doi.org/10.1257/0002828054825655

Anelli, M., Colantone, I., & Stanig, P. (2021). Individual vulnerability to industrial robot adoption increases support for the radical right. *Proceedings of the National*

Academy of Sciences, *118*(47), e2111611118. https://doi.org/10.1073/pnas.2111611118

Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent.". *Science*, *344*(6186), 843–851. https://doi.org/10.1126/science.1251868

Autor, D., Katz, L. F., & Kearney, M. S. (2008). Trends in U.S. wage inequality: Revising the revisionists. *The Review of Economics and Statistics*, *90*(2), 300–323. https://doi.org/10.1162/rest.90.2.300

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Barnes, L. (2022). Taxing the rich: Public preferences and public understanding. *Journal of European Public Policy*, *29*(5), 787–804. https://doi.org/10.1080/13501763.2021.1992485

Bremer, B., & Bürgisser, R. (2023). Do citizens care about government debt? Evidence from survey experiments on budgetary priorities. *European Journal of Political Research*, *62*(1), 239–263. https://doi.org/10.1111/1475-6765.12505

Busemeyer, M. R., Gandenberger, M., Knotz, C., & Tober, T. (2022). Preferred policy responses to technological change: Survey evidence from OECD countries. *Socio-Economic Review*. mwac015. https://doi.org/10.1093/ser/mwac015

Busemeyer, M. R., & Sahm, A. H. J. (2022). Social investment, redistribution or basic income? Exploring the association between automation risk and welfare state attitudes in Europe. *Journal of Social Policy*, *51*(4), 751–770. https://doi.org/10.1017/S0047279421000519

Busemeyer, M. R., & Tober, T. (2023). Dealing with technological change: Social policy preferences and institutional context. *Comparative Political Studies*, *56*(7), 968–999. https://doi.org/10.1177/00104140221139381

Caines, C., Hoffmann, F., & Kambourov, G. (2017). Complex-task biased technological change and the labor market. *Review of Economic Dynamics*, *25*, 298–319. https://doi.org/10.1016/j.red.2017.01.008

Cappelen, A. W., Moene, K. O., Sørensen, EØ, & Tungodden, B. (2013). Needs versus entitlements—An international fairness experiment. *Journal of the European Economic Association*, *11*(3), 574–598. https://doi.org/10.1111/jeea.12000

Charness, G., & Villeval, M.-C. (2009). Cooperation and competition in intergenerational experiments in the field and the laboratory. *American Economic Review*, *99*(3), 956–978. https://doi.org/10.1257/aer.99.3.956

Dermont, C., & Weisstanner, D. (2020). Automation and the future of the welfare state: Basic income as a response to technological change? *Political Research Exchange*, *2*(1), 1757387. https://doi.org/10.1080/2474736X.2020.1757387

Dimick, M., Rueda, D., & Stegmueller, D. (2018). Models of other-regarding preferences. Inequality, and redistribution. *Annual Review of Political Science*, *21*(1), 441–460. https://doi.org/10.1146/annurev-polisci-091515-030034

Durante, R., Putterman, L., & van der Weele, J. (2014). Preferences for redistribution and perception of fairness: An experimental study. *Journal of the European Economic Association*, *12*(4), 1059–1086. https://doi.org/10.1111/jeea.12082

Emmenegger, P., & Lierse, H. (2022). The politics of taxing the rich: Declining tax rates in times of rising inequality. *Journal of European Public Policy*, *29*(5), 647–651. https://doi.org/10.1080/13501763.2021.1993313

Emmenegger, P., & Marx, P. (2019). The politics of inequality as organised spectacle: Why the Swiss do not want to tax the rich. *New Political Economy*, *24*(1), 103–124. https://doi.org/10.1080/13563467.2017.1420641

Frey, C. B., Berger, T., & Chen, C. (2018). Political machinery: Did robots swing the 2016 US presidential election? *Oxford Review of Economic Policy*, *34*(3), 418–442. https://doi.org/10.1093/oxrep/gry007

Gallego, A., Kuo, A., Manzano, D., & Fernández-Albertos, J. (2022). Technological risk and policy preferences. *Comparative Political Studies*, *55*(1), 60–92. https://doi.org/10.1177/00104140211024290

Gallego, A., & Kurer, T. (2022). Automation, digitalization, and artificial intelligence in the workplace: Implications for political behavior. *Annual Review of Political Science*, *25*(1), 463–484. https://doi.org/10.1146/annurev-polisci-051120-104535

Gallego, A., Kurer, T., & Schöll, N. (2022). Neither left behind nor superstar: Ordinary winners of digitalization at the Ballot Box. *The Journal of Politics*, *84*(1), 418–436. https://doi.org/10.1086/714920

Gill, D., & Prowse, V. (2012). A structural analysis of disappointment aversion in a real effort competition. *American Economic Review*, *102*(1), 469–503. https://doi.org/10.1257/aer.102.1.469

Gingrich, J. (2019). Did state responses to automation matter for voters? *Research & Politics*, *6*(1), 1–9. https://doi.org/10.1177/2053168019832745

Goldin, C., & Katz, L. F. (2008). *The race between education and technology*. Harvard University Press.

Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *American Economic Review*, *99*(2), 58–63. https://doi.org/10.1257/aer.99.2.58

Hacker, J. S., Rehm, P., & Schlesinger, M. (2013). The insecure American: Economic experiences, financial worries, and policy attitudes. *Perspectives on Politics*, *11*(01), 23–49. https://doi.org/10.1017/S1537592712003647

Häusermann, S., Kurer, T., & Traber, D. (2019). The politics of trade-offs: Studying the dynamics of welfare state reform with conjoint experiments. *Comparative Political Studies*, *52*(7), 1059–1095. https://doi.org/10.1177/0010414018797943

Hope, D., & Limberg, J. (2022). The knowledge economy and taxes on the rich. *Journal of European Public Policy*, *29*(5), 728–747. https://doi.org/10.1080/13501763.2021.1992483

Hope, D., Limberg, J., & Weber, N. (2023). Why do (some) ordinary Americans support tax cuts for the rich? Evidence from a randomised survey experiment. *European Journal of Political Economy*, *78*, 102349. https://doi.org/10.1016/j.ejpoleco.2022.102349

Hope, D., & Martelli, A. (2019). The transition to the knowledge economy, labor market institutions, and income inequality in advanced democracies. *World Politics*, *71*(2), 236–288. https://doi.org/10.1017/S0043887118000333

Imai, K., Keele, L., Tingley, D., & Yamamoto, T. (2011). Unpacking the Black Box of causality: Learning about causal mechanisms from experimental and observational studies. *American Political Science Review*, *105*(4), 765–789. https://doi.org/10.1017/S0003055411000414

Iversen, T., & Soskice, D. (2001). An asset theory of social policy preferences. *American Political Science Review*, *95*(4), 875–893. https://doi.org/10.1017/S0003055400400079

Iversen, T., & Soskice, D. (2019). *Democracy and prosperity: Reinventing capitalism through a turbulent century*. Princeton University Press.

Jeffrey, K. (2021). Automation and the future of work: How rhetoric shapes the response in policy preferences. *Journal of Economic Behavior & Organization*, *192*, 417–433. https://doi.org/10.1016/j.jebo.2021.10.019

Kaplan, S. N., & Rauh, J. (2013). It's the market: The broad-based rise in the return to top talent. *Journal of Economic Perspectives*, *27*(3), 35–56. https://doi.org/10.1257/jep.27.3.35

Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors*. *The Quarterly Journal of Economics*, *107*(1), 35–78. https://doi.org/10.2307/2118323

Kurer, T. (2020). The declining middle: Occupational change, social status, and the populist right. *Comparative Political Studies*, *53*(10–11), 1798–1835. https://doi.org/10.1177/0010414020912283

Kurer, T., & Häusermann, S. (2022). Automation risk, social policy preferences, and political participation. In M. R. Busemeyer, A. Kemmerling, K. Van Kersbergen, & P. Marx (Eds.), *Digitalization and the welfare state* (pp. 139–156). Oxford University Press. https://doi.org/10.1093/oso/9780192848369.003.0008

Limberg, J. (2020). What's fair? Preferences for tax progressivity in the wake of the financial crisis. *Journal of Public Policy*, *40*(2), 171–193. https://doi.org/10.1017/S0143814X18000430

Mijs, J. J. B. (2021). The paradox of inequality: Income inequality and belief in meritocracy go hand in hand. *Socio-Economic Review*, *19*(1), 7–35. https://doi.org/10.1093/ser/mwy051

Moene, K. O., & Wallerstein, M. (2001). Inequality, social insurance, and redistribution. *American Political Science Review*, *95*(4), 859–874. https://doi.org/10.1017/S0003055400400067

Mummolo, J., & Peterson, E. (2019). Demand effects in survey experiments: An empirical assessment. *American Political Science Review*, *113*(2), 517–529. https://doi.org/10.1017/S0003055418000837

Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much?*. *The Quarterly Journal of Economics*, *122*(3), 1067–1101. https://doi.org/10.1162/qjec.122.3.1067

Philippon, T., & Reshef, A. (2012). Wages and human capital in the U.S. Finance industry: 1909–2006*. *The Quarterly Journal of Economics*, *127*(4), 1551–1609. https://doi.org/10.1093/qje/qjs030

Raven, J. (2000). The Raven's progressive matrices: Change and stability over culture and time. *Cognitive Psychology*, *41*(1), 1–48. https://doi.org/10.1006/cogp.1999.0735

Rehm, P. (2009). Risks and redistribution an individual-level analysis. *Comparative Political Studies*, *42*(7), 855–881. https://doi.org/10.1177/0010414008330595

Rehm, P. (2011). Social policy by popular demand. *World Politics*, *63*(2), 271–299. https://doi.org/10.1017/S0043887111000037

Saez, E., & Zucman, G. (2019). *The triumph of injustice: How the rich dodge taxes and how to make them Pay*. W. W. Norton & Company.

Scheve, K., & Stasavage, D. (2016). *Taxing the rich: A history of fiscal fairness in the United States and Europe*. Princeton University Press.

Scheve, K., & Stasavage, D. (2023). Equal treatment and the inelasticity of tax policy to rising inequality. *Comparative Political Studies*, *56*(4), 435–464. https://doi.org/10.1177/00104140221108

Schöll, N., & Kurer, T. (2024). How technological change affects regional voting patterns. *Political Science Research and Methods*, *12*(1), 94–112. https://doi.org/10.1017/psrm.2022.62

Stantcheva, S. (2021). Understanding tax policy: How do people reason?*. *The Quarterly Journal of Economics*, *136*(4), 2309–2369. https://doi.org/10.1093/qje/qjab033

Stiers, D., Hooghe, M., Goubin, S., & Lewis-Beck, M. S. (2022). Support for progressive taxation: Self-interest (rightly understood), ideology, and political sophistication. *Journal of European Public Policy*, *29*(4), 550–567. https://doi.org/10.1080/13501763.2020.1866054

Thewissen, S., & Rueda, D. (2019). Automation and the Welfare State: Technological change as a determinant of redistribution preferences. *Comparative Political Studies*, *52*(2), 171–208. https://doi.org/10.1177/0010414017740600

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). Mediation: R package for causal mediation analysis. *Journal of Statistical Software*, *59*(5), 1–38. https://doi.org/10.18637/jss.v059.i05

Varian, H. R. (1980). Redistributive taxation as social insurance. *Journal of Public Economics*, *14*(1), 49–68. https://doi.org/10.1016/0047-2727(80)90004-3

Walter, S. (2010). Globalization and the Welfare State: Testing the microfoundations of the compensation hypothesis. *International Studies Quarterly*, *54*(2), 403–426. https://doi.org/10.1111/j.1468-2478.2010.00593.x