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Fairness and Tax Preferences: A Conjoint Experiment

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ABSTRACT:

Experimental research on tax fairness has tended to focus on limited interpretations of fairness, and to do so by manipulating one attribute at a time.
This strategy tends to confound multiple questions and it impedes a comprehensive understan-ding of the relative importance of different conceptions of fairness. This paper addresses these limitations through a conjoint experiment that identifies the causal role ability to pay, deser-vingness and compensatory fairness considerations play in determining peoples' preferences for how the tax burden should be distributed, and how these preferences vary by respondent characteristics. In so doing, it presents the first evidence that compensatory arguments play an important role in determining tax preferences and have the capacity to garner support for progressive taxes as a way of compensating for the regressiveness of indirect taxation.

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In recent years, growing concern for income inequality in the United States has pushed the issues of taxation and redistribution to the center of public debate, attracting the interest of academics, policy-makers and society in general. As evidence of a recent and spectacular rise in inequality accumulates, policy-makers face increasing pressure to find policy solutions that will inevitably involve tax reform. The challenge, however, lies in designing a tax system that will simultaneously bridge partisan divisions and garner the support of domestic voters. A challenge that is compounded by a conspicuous lack of agreement both within and between the communities of policy-makers and scholars regarding what makes citizens support certain tax schemes.

Policy-makers are starkly divided on the question of how taxes should vary with respect to income, or more specifically, how much taxes it is both fair and efficient to charge the rich, with Democrats favoring more progressive taxes than Republicans[1]. Scholars, on the other hand, agree on the fact that tax preferences are determined by both self-interest and fairness considerations, but disagree on the best way to characterize the latter. As opposed to policy-makers, their discussion has lately focused on the role of deservingness, as determined by sources of income, rather than levels of income. In consequence, we lack a comprehensive assessment of the role different fairness considerations play in determining peoples' preferences for how the tax burden should be distributed. In its absence, it will remain difficult to design reforms that can enjoy widespread support. The purpose of this paper is to present a conjoint survey experiment that will provide such a comprehensive assessment.

Conjoint survey experiments have proven particularly useful for measuring preferences and uncovering the determinants of multi-dimensional decision making (see for example Ballard-Rosa et al. (2017); Hainmueller and Hopkins (2015); Bansak et al. (2016); Bechtel and Scheve (2013); Bernauer and Gampfer (2015)). In this case, I run a conjoint experiment on a sample of 2,000 Amazon Turk respondents with the purpose of examining what fairness considerations people use when deciding how to distribute the tax burden, how these considerations vary across different groups of voters and ultimately, what justifications might be able to garner public support for which types of tax systems.

Preferences regarding the distribution of the tax burden can be determined by at least three factors. First, preferences can be determined by self-interest, meaning people simply prefer systems that maximize their own (current or expected) income.

[1] See for example The Wall Street Journal, "The GOP's 'Tax the Rich' Temptation", October 8th 2017, https://www.wsj.com/articles/the-gops-tax-the-rich-temptation-1507487704 (accessed October 13th 2017), and The New York Times, "I.M.F. Cautions Against Tax Cuts for the Wealthy as Republicans Consider Them", October 11th 2017, https://www.nytimes.com/2017/10/11/us/politics/imf-tax-cuts.html (accessed October 13th 2017).

Second, preferences can be determined by efficiency, meaning people prefer systems that can collect the most taxes at a lower cost (where the cost is usually thought of in terms of the distortions introduced by taxes into individuals' economic behavior). Finally, and of particular relevance here, preferences can be determined by fairness concerns, meaning people prefer systems that distribute the tax burden in a manner that is in accordance with their conception of fairness.

The experimental design used in this paper presents respondents with information regarding three attributes of hypothetical tax-payers (level of income, source of income, and percentage of income paid in sales taxes), and asks them to choose out of a pair which one should pay a higher income tax rate than the other[2]. This allows me to directly test the role ability to pay, deservingness and compensatory fairness considerations play in determining tax preferences, while indirectly examining the influence of self-interest, efficiency and other fairness considerations (inequality aversion and equal treatment) on their decisions.

The paper makes two main contributions to the literature on fairness and tax preferences. On the one hand, it provides the first measure of the influence of compensatory arguments -which advocate for the use of taxes to compensate for unequal interventions by the state- on tax preferences. This allows for a richer scholarly understanding of peoples' conceptions of deservingness and fairness in taxation. On the other hand, it enables the comparison of different fairness considerations by placing them on the same scale in terms of how important they are to citizens when it comes to deciding how to distribute the tax burden. This is of particular importance to policy-makers, as it highlights potential strategies to develop tax instruments that enjoy higher levels of legitimacy and ultimately, support[3].

Findings indicate that ability to pay, deservingness and compensatory fairness considerations all matter, but they do so to different extents for different sets of respondents. Overall, ability to pay considerations, based on level of income, can have the largest effect on the probability that a profile will be chosen, but are marred by disagreements between conservatives and liberals. In fact, the general pattern of preferences revealed by subgroup analyses supports the notion that ideological divisions are based on deep-rooted differences in conceptions of justice, with conservatives placing more emphasis on the fairness of procedures and liberals on that

[2]In terms of scope, this paper therefore focuses on how the tax burden is allocated, which has a direct effect on the distribution of income in society, and is a fundamental component -and point of contention- in the design of tax systems. The other fundamental component in the design of tax systems, the overall level of revenues to be collected, will not be addressed. Similarly, while fairness in taxation can involve both how the tax burden is assigned and how tax revenues are distributed, my focus is on the former.

[3]In light of what the responsiveness literature has taught us regarding the substantial impact of public opinion on policy, particularly on salient matters such as tax reform (Burstein, 2003; Stimson et al., 1995), this may be especially relevant.

of outcomes. Moreover, findings also reveal two strategies that have the potential to overcome political cleavages and garner widespread support for more progressive taxation: compensatory arguments which use direct taxes to compensate for the regressiveness of indirect taxation, and deservingness arguments for taxing high incomes resulting from one's social background. Finally, the experiment reveals that fairness in taxation does not only involve equalizing outcomes or rewarding effort, but also punishing undesirable behavior.

The paper is organized as follows. Section 1 discusses the literature on tax fairness, highlighting its main findings, approaches and limitations. Section 2 presents the design of a conjoint survey experiment intended to address these limitations. Section 3 introduces estimation strategies and describes the main results of the experiment. Section 4 describes the diagnostic and robustness tests conducted, and their results. Section 5 concludes.

1 What is Tax Fairness?

The literature on redistribution has examined the role of a host of individual-level characteristics (including partisanship, self-interest, income mobility, beliefs about the efficiency of taxation, beliefs about how income is produced, racial attitudes, risk preferences, altruism, religiosity, reciprocity, and aversion to inequality) in determining preferences for the level and distribution of taxes[4]. As with economic theory in general, one of the main findings of this research has been that preferences are not only motivated by material self-interest, but also by concerns for fairness (Alesina and Angeletos, 2005; Alesina et al., 2012; Alesina and Giuliano, 2009; Durante et al., 2014; Esarey et al., 2011; Fong, 2001; Fong and Luttmer, 2011).

What we do not know that much about though, is what types of fairness considerations are used, by whom, and what their relative importance is. In the literature, fairness is usually conceptualized as deservingness (or perceived worthiness) and, to a lesser extent, inequality aversion; both of which have been studied using formal, observational and experimental methods.

Deservingness refers to the notion that depending on how income (or wealth) is produced, some people are more deserving of their income than others, and those who are more deserving should be entitled to retain a higher share of it (through lower taxes), than those who are less deserving. This idea of deservingness has been operationalized in two distinct ways in the literature. On the one hand, formal and observational studies have focused on the role of abstract beliefs about how income is produced to show that people who believe income is the result of effort prefer lower

[4]see Alesina and Giuliano (2009) for a review of this literature.

taxes than those who believe it is the result of luck. These beliefs have most notably been used to explain differences regarding the preferred level of taxation in the US and Europe (Piketty, 1995; Alesina and Angeletos, 2005; Alesina and Glaeser, 2004). On the other hand, experimental studies have manipulated the source of income to show that subjects prefer higher taxes when income results from luck than when it results from effort (Durante et al., 2014; Fong and Luttmer, 2011; Chow and Galak, 2012; Lefgren et al., 2016). Durante et al. (2014) expand upon this distinction to include income resulting from initial conditions or opportunity, and find that it results in intermediate levels of taxation (larger than effort but smaller than luck).

Inequality aversion refers to the fact that a more equitable allocation of outcomes in society increases the utility of some individuals, making them willing to give up some material payoff to move in this direction (Fehr and Schmidt, 2006; Alesina and Giuliano, 2009; Fehr and Schmidt, 1999). Ultimately however, these views are often found to be grounded on ideas of deservingness, in the sense that people who think income results from luck are more inequity averse than those who think it results from effort (Esarey et al., 2011). Moreover, studies focusing on the influence of contextual characteristics on inequality aversion argue that this effect works through changes in beliefs about deservingness (i.e., exposure to inequality causes people to doubt the extent to which income results from effort and therefore support more redistribution) (McCall et al., 2017). In a recent paper, Lü and Scheve adopt a different approach to show that individuals "do not care about inequality generally but are interested in the fairness of their own outcome relative to others" (Lü and Scheve, 2016, p. 1967).

In general, the studies mentioned above are based on a rather restrictive view of fairness considerations in taxation, limited to whether taxable income or wealth were earned "fairly", or whether the existing level of inequality is considered fair. In their 2016 book, Scheve and Stasavage provide a wider framework for understanding the role played by fairness considerations in determining tax preferences. They argue that while everyone agrees that taxes should be fair and the state should treat citizens as equals, "there are multiple ways to plausibly treat people as equals in taxation, and this is what debating tax fairness is all about" (Scheve and Stasavage, 2016, p. 7). They go on to discuss the three arguments that historically have been most commonly used in this debate: equal treatment, ability to pay and compensation. Equal treatment supporters argue that since all citizens are equal, the same policy should apply to everyone, which in terms of taxation translates into a flat or proportional tax[5], where everyone pays the same rate. Ability to pay supporters argue that treating people as equals implies demanding the same level of sacrifice from them, and since one dollar in taxes does not represent as much sacrifice to a

[5]In theory, equal treatment supporters could also endorse a fixed tax in which everyone pays the same amount, but in practice this rarely happens.

rich person as to a poor person, the rich should pay a higher tax rate. Historically, these types of arguments have been used to justify progressive taxation. Finally, compensatory arguments look at the broader context of government intervention in the economy and maintain that if interventions by the state privilege a certain group, that group should pay higher taxes to compensate for that privilege and restore equal treatment. In practice this argument has also been used to justify progressive taxes that compensate for state interventions that placed the rich in a privileged position. In fact, Scheve and Stasavage (2016) argue that this was the argument used to justify the highest levels of tax progressivity imposed during the 20th century in the context of mass mobilization wars[6]. They also show that even before that -as early as the nineteenth century-, compensatory arguments were used to promote progressive taxation as a way of compensating for the regressive incidence of consumption taxes.

This distinction between equal treatment, ability to pay and compensatory arguments is based on a historical review of policy debates and the arguments presented therein. Scheve and Stasavage (2016) do not however directly test the role played by these different fairness considerations in determining actual individual preferences for taxation. Nonetheless, the role of ability to pay (as opposed to equal treatment) has been tested empirically, finding "strong evidence that the American public has progressive tax preferences on average, disliking taxes on the poor while favoring higher tax rates on the rich" (Ballard-Rosa et al., 2017, p. 2).

Overall, existing experimental research has focused on the role of level of income (Ballard-Rosa et al., 2017), source of income (Durante et al., 2014; Krawczyk, 2010), and inequality aversion (Lü and Scheve, 2016; Chow and Galak, 2012) (as opposed, in each case, to self-interest); and it has done so by manipulating one attribute at a time[7]. As a result, three limitations of this literature can be noted. The first is that the role of compensatory arguments has not been tested empirically. The second is that because they are always studied separately, we do not have a full understanding of the relative importance of and potential interactions between these conceptions of fairness (i.e., which one do people care more about? are sources of income only important within income groups?). The third is that previous research suffers from

[6]In this context compensatory arguments were used to justify high taxes on the rich (or the conscription of wealth) as a way of matching the conscription of labor, and compensating for the fact that some of the rich were in fact benefitting economically from the war industry (Scheve and Stasavage, 2016).

[7]One noteworthy exception is the work by Lefgren et al. (2016), which varies both reward (high vs low) and effort (high vs low). However, their work examines peoples' preferences for rewarding effort (by focusing on the interaction between the level of effort and reward), rather than disentangling the effect of each. Moreover, taxes are fully redistributive in their setting and participants are parties to this redistribution, raising additional concerns regarding their relative performance within the group

two forms of confounding. On the one hand, and as a result of studying fairness conceptions individually, there can be confounding between level and source of income, as people infer the latter from the former (i.e., people assume that rich people earned their wealth through effort). On the other hand, and as a result of focusing on the broad distinction between effort and luck, there can be confounding in the effects of luck, as some people can interpret it as pure random luck (e.g., winning the lottery), others as linked to a person's social background (e.g., being born in a rich family), and others as resulting from state action (e.g., benefitting from special legislation).

The experimental design presented here seeks to overcome these three limitations by i) assessing whether a specific form of state benefit (the unequal distribution of the sales tax burden) raises compensatory concerns; ii) randomly varying level and source of income; iii) specifying four distinct sources of income (luck, effort, social background and state benefit); and iv) comparing the effects of each of these fairness considerations on the same scale. Because this is the first empirical test of the role of compensatory arguments, they are assessed in two different ways. On the one hand, they are considered to be part of the broader deservingness debate by expanding the distinction between effort and luck to include a new dimension: state benefit. On the other hand, I also directly test whether the unequal distribution of the burden of the sales tax (which disproportionately affects the poor) triggers compensatory concerns in a way similar to that described by Scheve and Stasavage (2016) in the nineteenth century[8]. Furthermore, these authors conclude that by highlighting the regressive incidence of consumption taxes, compensatory arguments could be used to garner support for more progressive taxation today, an important argument which this experiment directly tests.

2 Experimental Design

I use a conjoint design to identify which individual attributes people take into consideration when deciding how to distribute the tax burden, as a way of getting at which fairness considerations they are applying. Conjoint survey experiments "ask respondents to choose from or rate hypothetical profiles that combine multiple attributes, enabling researchers to estimate the relative influence of each attribute value on the resulting choice or rating" (Hainmueller et al., 2014, p. 2). In this case, respondents were presented with pairs of profiles in which income level, source of income, and percentage of income paid in sales taxes were randomly varied, and asked to choose which one of these profiles should pay a higher tax rate. The main

[8]The idea being that because one tax should compensate for another, "any form of direct tax, such as an income tax, ought to take a progressive form in order to compensate for the regressive incidence of indirect taxes" (Scheve and Stasavage, 2016, p. 39).

intuition behind this design is that if people apply ability to pay considerations (i.e., they think richer people should pay more taxes) they should choose on the basis of level of income; if they apply deservingness considerations (i.e., they think people who did not exert effort should pay more) they should choose on the basis of source of income; and if they apply compensatory considerations (i.e., they think people who have benefitted from the state should pay more) they should choose on the basis of whether the source of income resulted from state benefit and/or the percentage of income paid in sales taxes[9].

This design offers several advantages. The fact that attributes vary randomly allows me to disentangle the effects of correlated attributes (e.g., wealth and effort). As opposed to asking respondents to directly assign a tax rate to each profile, the forced choice component neutralizes attitudes about the overall level of taxation and identifies the attributes that make citizens appear as more or less taxable to the respondent. Since the resulting estimates represent effects on the same outcome (the probability that a profile will be chosen to receive the higher tax rate), they can be compared in order to assess the relative influence of different attributes (and ultimately, fairness considerations). The fact that the intended use of the revenue collected is left unspecified means I can focus on how the tax burden is distributed, under the assumption that "due to random assignment, the distribution of beliefs about spending should be balanced across treatment groups and should not affect the internal validity of our estimates" (Ballard-Rosa et al., 2017, p. 4). In addition, this design also allows me to assess the existence of heterogeneity in preferences by respondent characteristics, and the extent to which attributes interact with each other. Finally, research indicates that the paired profiles conjoint design performs remarkably well in capturing the structural effects of attributes that drive real world behavior (Hainmueller et al., 2015).

Table 1 presents the attribute levels that were randomly assigned to profiles in the survey[10]. Income and percentage of income paid in taxes varied discretely from low to high, while sources of income represent effort, luck, state benefit and social background[11] and were chosen so as to be independent of level of income.

[9] It is not immediately clear whether both will matter, as it may be the case that people want to compensate for a state benefit, but do not perceive the unequal incidence of the sales tax as one.

[10] To see the complete survey go to `https://nyu.qualtrics.com/jfe/preview/SV_ehfLU3JUO4VDDaR?Q_CHL=preview`

[11] Sources of income used were the subject of a formative study which sought to identify sources of income that would be interpreted as resulting from effort, luck, state benefit and social background, and were relatively orthogonal to one another. See Appendix (A) section A.1 for details.

Table 1: Attributes and Attribute Levels

Attribute	**Attribute levels**
Annual income	\$30,000, \$80,000, \$150,000
Source of income	Started own small business, Receives annuity from a lottery prize, Owns business that was bailed out by government, Got a job through family connections
% of income paid in sales taxes	1%, 5%, 10%

In terms of presentation, two profiles were presented side-by-side on the same screen, with the following prelude:

> Many observers in the United States have discussed the possibility of changing the federal income tax code to address multiple issues. The design of a new tax system raises a number of questions, including whether and why some people should pay higher rates than others. We are interested in what you think about this.
>
> We will show you profiles of random individuals. You will be shown pairs of individuals, along with several of their attributes. For each comparison we would like to know which of the two individuals you think should pay a higher tax rate. In total, we will show you five comparison pairs.
>
> Bear in mind that when we talk about tax rates we mean the percentage of their income that someone pays in taxes. People with different incomes who pay the same rate actually pay different amounts (i.e., 30% of an income of \$100,000 is \$30,000, but of an income of \$50,000 it is \$15,000).
>
> Please take your time when reading the attributes of each individual. People have different opinions about this issue, and there are no right or wrong answers.

This introduction was followed by a screen similar to figure 1.

Figure 1: Example of choice-based conjoint survey

Attributes	Individual 1	Individual 2
Source of income	Got a job through family connections	Started own small business
Percentage of income paid in sales taxes	10%	5%
Annual income	$30,000	$150,000

Which of the two individuals would you personally prefer to charge a higher tax rate to?

Individual 1

Individual 2

In order to maximize the number of observations and allow respondents to familiarize themselves with the format of the experiment, each subject saw 5 pairs of profiles. After the first pair of profiles, they were asked to answer the following open ended question, which provided supplementary information on respondents' preferences and allows me to adjudicate between fairness and efficiency concerns:

> Why did you choose citizen <chosen citizen>?

After completing their 5 choice tasks, respondents were asked to fill a survey asking for their socio-demographic information (age, gender, education, household income, partisanship, employment status, race, marital status, ideology and zip code of residence), which was used to check for heterogeneous preferences. They were also asked to answer a question regarding their general preferences for progressivity, used to measure adherence to equal treatment, and a question regarding their opinion about current levels of inequality, used to determine whether they are inequality averse:

> Do you think everyone should pay the same share of their income in taxes or some people should pay a higher share than others?
>
> American households with incomes in the top 10% earn an average of $230,000 per year, and households with incomes in the bottom 50% earn

an average of $25,000 per year. Should this difference be bigger, smaller, or about what it is now?

The survey was conducted in October 2017 on an online sample of 2,000 US residents on Amazon's Mechanical Turk (MTurk)[12]. Previous studies have shown that relative to other convenience samples often used in experimental research in political science, MTurk subjects pay more attention (Berinsky et al., 2014) and are more representative of the general population (Berinsky et al., 2012). Nonetheless, my MTurk sample is considerably younger, better educated and more liberal than the population (see Appendix section A.2 for a comparison). In order to address some concerns regarding the external validity of my findings, entropy balancing weights are used to adjust the sample so that it matches the demographic and geographic margins of the adult population, as described in the Appendix.

3 Analysis and Results

Outcome data come from the forced choice made by respondents regarding which profile in each pair should pay a higher tax rate. The unit of analysis is thus the individual profile and outcomes are measured using a dummy variable that takes a value of 1 if a profile is chosen and 0 if a profile is not chosen. With a sample of 2,000 respondents the total number of observations is therefore equal to 20,000 (2,000 respondents $*$ 5 tasks $*$ 2 profiles per task). After removing uninformative responses[13], my dataset comprises 18,922 observations from 1946 different respondents.

Table 2 presents a simple crosstabulation of the outcome variable, choice, by attribute levels. As we can see, profiles with the lowest level of income are least likely to be selected for the higher tax rate, and the share of profiles selected increases with income. Similarly, looking at source of income, profiles whose income results from effort are selected least, while those whose income results from luck are selected most. These results are all in line with previous findings regarding ability to pay (Ballard-Rosa et al., 2017) and deservingness (Durante et al., 2014; Fong and Luttmer, 2011; Lefgren et al., 2016) considerations. In the case of the percentage of income paid in sales taxes, we find that profiles with the highest percentage (10%) are selected least, and selection increases as the share of income paid in sales tax decreases, which is in line with compensatory arguments. For each attribute, the levels with the lowest percentage of selection ($30,000 annual income, effort and 10% paid

[12] The design was preregistered in the Political Science Registered Studies Dataverse (doi:10.7910/DVN/QKYQF5).

[13] I excluded respondents who completed the survey in less than half of the median time (226 seconds), and I also excluded choices from pairs in which both profiles had the same attributes.

in sales taxes) will be used as baselines in the statistical analyses to follow, which will allow me to conduct hypotheses tests of the difference in probability of selection between these baselines and the other attribute levels.

Table 2: Distribution of Choice by Attribute Levels

Attributes	Choice (%) 0	1
Level of Income		
$30,000	73.8	26.2
$80,000	48.11	51.89
$150,000	28.42	71.58
Source of Income		
Effort	66.15	33.85
Social background	52.33	47.67
State benefit	40.97	59.03
Luck	40.95	59.05
% Paid in Sales Taxes		
10%	58.67	41.33
5%	51.17	48.83
1%	40.15	59.85

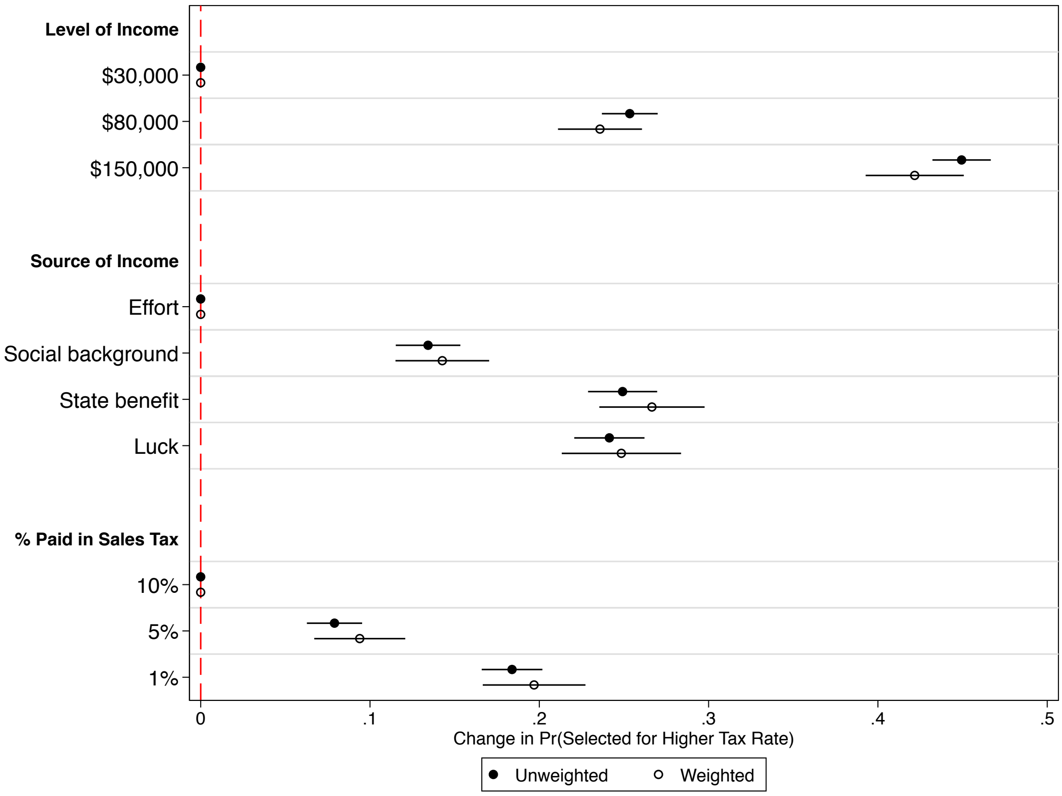
My benchmark regression model will thus estimate the Average Marginal Component Effects (AMCEs) for each attribute value, pooling across all respondents. AMCEs measure the average causal effect of a given attribute value on the probability that a profile will be chosen, compared to the baseline attribute value. Because regressors are in expectation orthogonal to one another, AMCEs can be estimated via a single OLS regression of the outcome variable on dummies for each level of each attribute (excluding the reference categories), with standard errors clustered by respondent to account for within-respondent correlation[14]. The AMCE for each attribute level will be equal to the estimated coefficients on their dummies (Hainmueller et al., 2014).

Figure 40 presents the pooled weighted and unweighted results. As usual, dots represent point estimates and lines represent 95% confidence intervals. These results indicate that all three attributes -level of income, source of income and share of income paid in sales tax- have an effect on respondents' decision regarding how to

[14]Formally, the regression model estimated is
$choice_{ijk} = \beta_0 + \beta_1 I2_{ijk} + \beta_2 I3_{ijk} + \beta_3 S2_{ijk} + \beta_4 S3_{ijk} + \beta_5 S4_{ijk} + \beta_6 T2_{ijk} + \beta_7 T3_{ijk} + \varepsilon_{ijk}$
Subscripts i identify respondents, j identify the profile in each pair ($j = 1, 2$), and k identify the task ($k = 1, 2, 3, 4, 5$).

distribute the tax burden. Moreover, the magnitude of these effects is sizeable, as they increase the probability of selection by at least 8 and as much as 45 percentage points, with respect to the baselines.

Figure 2: Effect of Profile Attributes on Probability of Being Selected for Higher Tax Rate



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent. Bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

In accordance with ability to pay concerns, the probability of being chosen to pay the higher tax rate increases monotonically with level of income. Moreover, profiles with the highest income have the largest probability of being selected -72%, approximately 45 percentage points higher than profiles with the lowest income-. On the other hand, as the moderator analysis will show, ability to pay considerations give rise to important political disagreements.

It could be argued that choices based on level of income express motivations driven by efficiency rather than fairness concerns, as respondents simply choose the high-income profiles to maximize revenue. The fact that other attributes also have an effect suggests that results are not entirely driven by efficiency. Moreover, the justifications given in response to the open-ended question in the survey indicate that decisions were largely driven by fairness and not efficiency concerns. Not only did respondents overwhelmingly explain their decisions in terms of the fairness concerns hypothesized; the most sparing among them simply said they chose profile x because it was fair. Furthermore, out of all 1946 respondents, only 8 justifications seemed to align with efficiency concerns. Justifications for choices made on the basis of level of income were usually framed in terms of ability to pay by saying taxes will be less of a burden/hardship to that person, or that she can better afford them.

Sources of income also matter, and in the way predicted by the deservingness literature: those whose income results from effort have the least probability of being selected, this probability is highest for those with luck, and those benefitting from their social background are somewhere in between. Moreover, justifications clearly reference the extent to which people "earned" their income or worked hard for it. The novel finding here is that people care a lot about compensating for a state benefit. In fact, the effect of state benefit is as large as that of luck, increasing the probability of selection by approximately 25 percentage points with respect to the baseline (effort). Moreover, 61% of all the profiles including this source of income were selected, and this percentage only falls to 42% when it was combined with the lowest level of income, indicating respondents think beneficiaries of a bailout should pay higher taxes even if they have low income. This finding highlights the importance of compensatory arguments in explaining tax preferences, and the need for studies of deservingness to expand upon the basic effort-luck distinction. Furthermore, justifications based on state benefit are particularly enlightening as they reveal the existence of two groups of respondents. One group thinks individuals who benefitted from a bailout deserve to pay the higher tax rate in order to pay back what they owe the government (i.e., restore equal treatment). Another group thinks individuals who benefitted from a bailout deserve to be punished for not having been able to run their business properly and taking money from the government. This use of taxes as punishment for behavior that is considered lacking is consistent with Di Tella et al. (2017), who find that respondents use high taxes to punish corrupt businesspeople. Moreover, it reminds us that while fairness is often linked to altruism (in the sense that people derive utility from others' material gains), it also involves an inclination to punish those who are perceived as dodging their fair share of societal burden, as shown by Fehr and Gächter's seminal public goods experiment (2000).

Moving on to the effect of the percentage of income paid in sales tax, results indicate that it is also monotonic, as would be expected from the application of compensatory arguments. In addition, as will be shown below, this attribute presents two particularities which substantiate Scheve and Stasavage's expectation that it might be used to build support for more progressive taxation (2016). In the first place, unlike most other attributes, there is a strong consensus regarding the importance of percentage paid in sales taxes. That is to say, these results do not present significant variation across different politically relevant groups, expressing a general agreement that surpasses even class and party cleavages. In the second place, both choices and justifications show respondents have a strong commitment to horizontal and vertical equity, as they seek to equalize tax rates whenever income levels are the same, and dislike the combination of high income and a low share paid in sales tax. This commitment to vertical equity could well be mobilized politically given that indirect taxes are in fact regressive, meaning high-income groups do pay a lower percentage of their income in sales taxes than low-income groups[15]. Moreover, although the effect of 1% paid in sales tax is smaller, profiles with this attribute turn out to be just as likely to be selected as profiles with state benefit or luck as source of income (due to differences in baseline levels), with a probability of selection of almost 60%.

Finally, it is also worth noting that source of income and share of income paid in sales tax did not operate as subsidiary criteria, used only when levels of income were equal. In fact, 45% of the choices that were made on the basis of source of income or taxes paid included profiles with different income levels.

As can be seen in figure 40, using post-stratification weights to make my sample more representative of the population does not significantly change these results. However, the use of weights does increase the variance of my estimates, as expressed in the larger confidence intervals in figure 40. Therefore, in what follows I will present unweighted results. This prevents me from paying the variance penalty, which becomes more relevant in the moderator analyses presented below. Nonetheless, weighted results can be found in section A.4 of the Appendix.

3.1 Moderator Analyses

In addition to the pooled results, my survey design also allows me to examine two types of interactions: between respondents' background characteristics and the causal effects of an attribute; and between attributes themselves. The former, es-

[15]According to the Institute on Taxation and Economic Policy, on average across all states, families in the lowest 20% in the income distribution pay 7% of their family income on sales and excise taxes, while families in the top 1% only pay 0.8% of their income. Moreover, in some states the share paid by low-income families is as high as 12.6% (Washington) and the share paid by top income families is as low as 0.1% (Montana) (Davis et al., 2015).

timated using conditional AMCEs, allow me to test whether different subgroups of respondents exhibit different preferences, while the latter allow me to test whether the effect of an attribute depends on the value of a different attribute. I will start by using conditional AMCEs to investigate the effect of other potential determinants of tax preferences discussed in the literature: self-interest, inequality aversion and equal treatment.

How might self-interest affect respondents' choices? One possibility[16] is that in accordance with a desire to minimize their tax burden, high-income respondents will be less likely than low-income respondents to distribute the tax burden on the basis of level of income. Instead, high-income respondents will be more likely to make their choices on the basis of other attributes[17]. Figure 3 presents the AMCE estimates for subsamples of respondents with different income levels and corroborates these expectations, lending support to the idea that -as is usually the case in the literature-respondents decide not only on the basis of fairness considerations, but also of their self-interest. In particular, respondents with high incomes have a probability of selecting the profile with the highest annual income that is 9 percentage points lower than that of respondents with low incomes, while their probability of selecting on the basis of source of income is between 5 and 12 percentage points higher[18]. These results are broadly in line with the predictions of the Meltzer-Richard model (1981), as it relates position in the income distribution to preferences for redistribution[19].

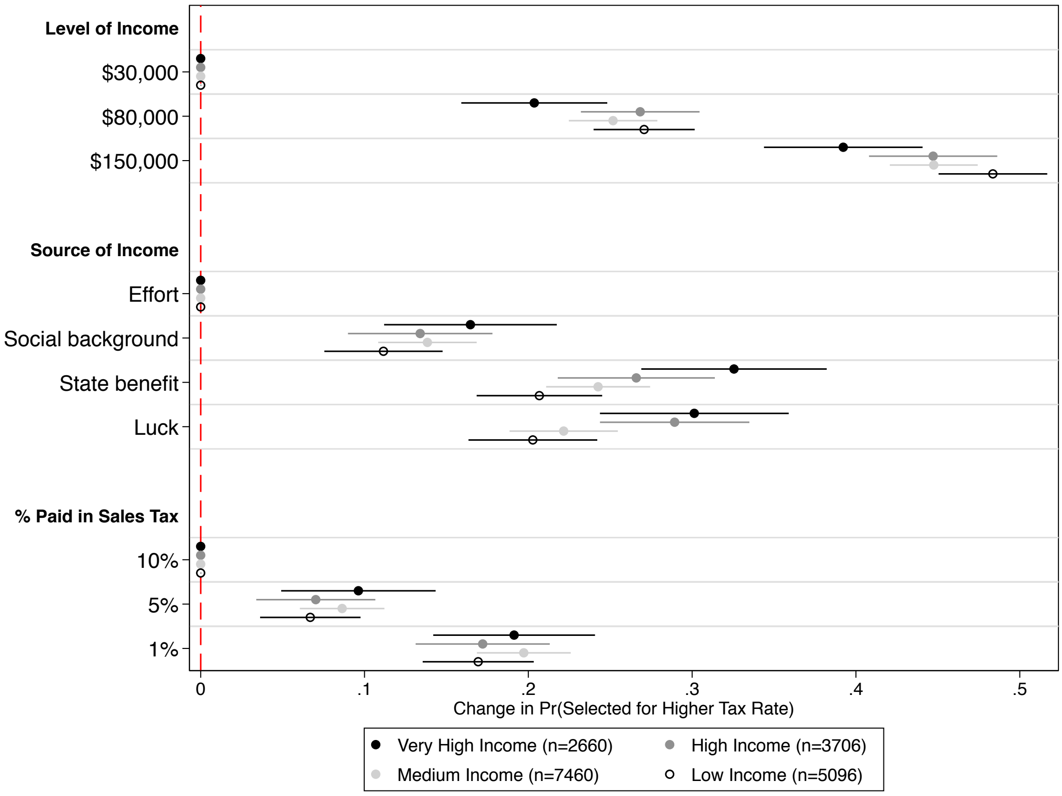
[16]Another possibility I examined focuses on the choices of respondents who might identify with the income levels presented in the experiment. The idea here is that if self-interest plays a role, respondents with incomes around $30,000 are free to choose based on level of income because this choice will not directly affect them; respondents with incomes around $80,000 are less likely to choose based on this level of income, but may choose profiles with the highest level of income; while respondents with incomes around $150,000 are less likely to choose profiles based on level of income at all. Figure 25 in the Appendix presents the results, showing income groups behave as expected, but differences between them are not significant.

[17]If high-income respondents are conscious of the fact that they actually pay a lower share of their income in sales tax than lower earners, they would probably not choose on the basis of this attribute either. However, it is not clear to what extent they are aware of this.

[18]Note that according to psychological research by Davidai and Gilovich (2015) conservatives and low-income respondents tend to believe there is more income mobility than liberals and high-income respondents. In consequence, they also perceive the system as fairer (in the sense that everyone gets their just deserts) and one would expect them to perceive a smaller need for redistribution from the rich to the poor and therefore to care less about level of income. My results indicate this is indeed the case for conservatives, but not for low-income respondents, suggesting self-interest offsets these fairness considerations among low-income respondents.

[19]With the caveat that the Meltzer-Richard model refers to the level of redistribution resulting from the magnitude of a proportional -rather than the steepness of a progressive- tax (Meltzer and Richard, 1981).

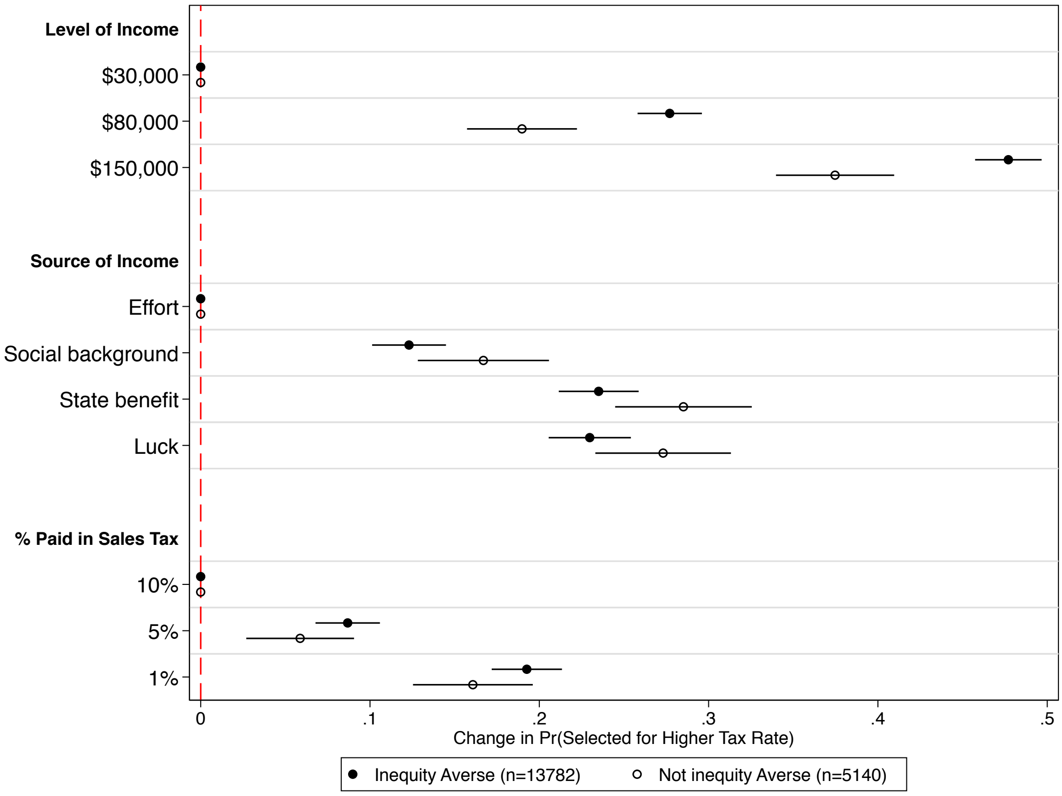
Figure 3: Effect of Profile Attributes by Respondent Income Level



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for four different groups of respondents: those with annual incomes of $125,000 or above (very high income), between $80,000 and $124,999 (high income), between $30,000 and $79,999 (medium income), and under $30,000 (low income). The points without horizontal bars denote the attribute value that is the reference category for each attribute. This analysis not included in pre-analysis plan.

According to the literature, there are two main ways in which inequality aversion might affect peoples' tax preferences. The first maintains that individual beliefs about acceptable levels of inequality will make preferences more redistributive. Figure 4, which presents my estimates broken down by respondents' subjective evaluations regarding current levels of inequality, supports this notion. As we can see, inequality averse respondents are significantly more likely to select the profiles with higher income, in accordance with ability to pay progressive taxes.

Figure 4: Effect of Profile Attributes by Respondent Inequality Aversion



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those who think current levels of inequality are too high (inequality averse), and those who think they are either too small or about right (not inequality averse). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Alternatively, inequality aversion might be conceived to be determined by exposure to inequality, such that respondents who are exposed to higher levels of inequality have more progressive preferences (as in McCall et al. (2017)). My results also lend support to this notion[20], with respondents living in zip codes with higher levels of

[20] It is worth noting that recent experimental research finds exposure to inequality reduces support for redistribution among people with high-incomes (Sands, 2017; Côté et al., 2015). On the other hand, Rueda and Stegmueller argue that the rich prefer higher levels of redistribution in more unequal regions, as a way of reducing a negative externality of inequality: crime (2016). Breaking down results by level of income (an analysis not comprised in my pre-analysis plan), I find that high income respondents' reliance on level of income tends to be stable, whereas among low

inequality exhibiting a larger effect of level of income than those living in zip codes with lower levels of inequality (see Appendix figure 20 for results)[21].

The equal treatment question in the post-experimental survey reveals that 32% of respondents think everyone should pay the same share of their income in taxes[22]. This is consistent with previous estimates, which put the share of flat-raters at around 28% of respondents (Scheve and Stasavage, 2016). These supporters of equal treatment do not select profiles randomly though. Both their choices[23] and their justifications indicate that despite preferring a flat rate, when forced to choose they do have preferences regarding the fairest way to distribute the tax burden. Figure 5 shows that equal treatment supporters are much less likely to adhere to ability to pay and more likely to select profiles on the basis of deservingness and compensatory arguments.

As mentioned above, conditional AMCEs can also be estimated to examine whether different groups in the population have different preferences, indicating a reliance on different conceptions of fairness. The Appendix section A.3 presents results using all of the demographic information collected in the post-experimental survey (age, gender, marital status, race, citizenship, education level, employment status, party identification, ideology and vote choice in the 2016 presidential elections). Here, I will only comment on the most stark inter-group differences as determined by race, gender and party identification, and one noticeable absence of differences. In terms of the latter, results indicate that although respondents with higher education seem to care more about sources of income than respondents with lower education (up to high school), there are no significant differences between them[24]. This finding is interesting as it suggests fairness considerations are not determined by political or cognitive sophistication.

income respondents reliance on level of income increases with local inequality. This suggests the effect found here may be driven by Newman et al.'s activated disillusionment hypothesis (2015), which argues that exposure to high inequality leads people with low incomes to perceive the system as less meritocratic or fair.

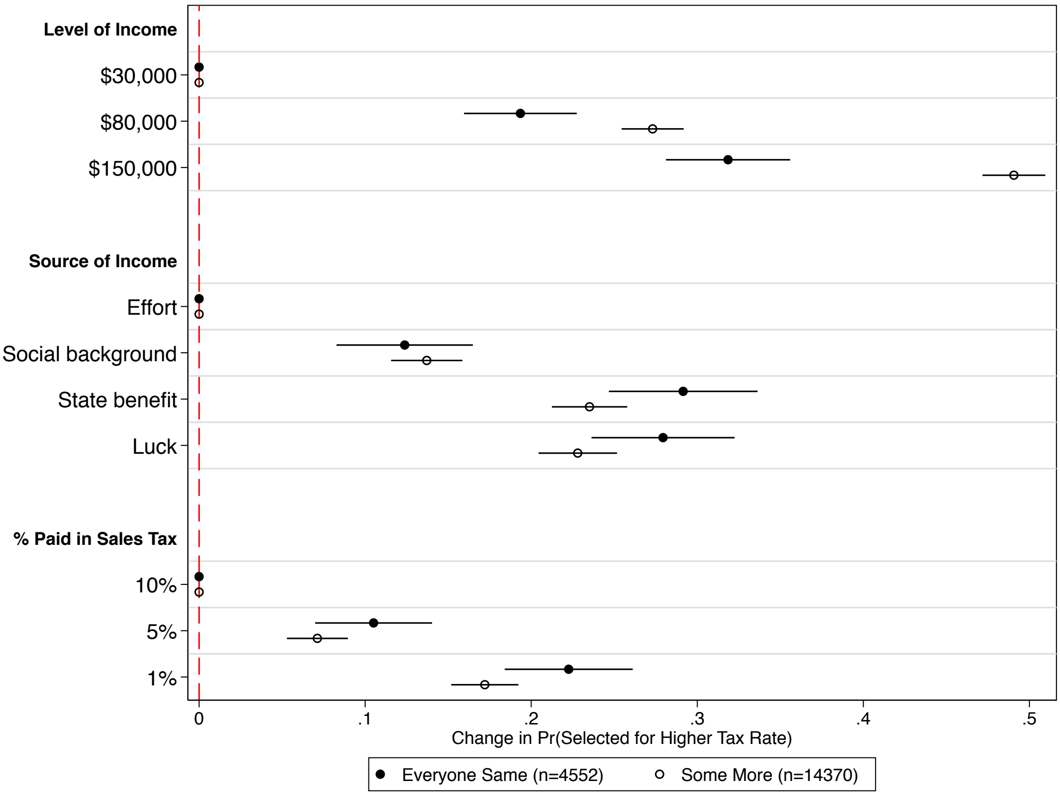
[21] I also checked whether differences in state-level inequality affected results, but they did not, as shown in figure 21 of the Appendix.

[22] In my MTurk sample respondents who support equal treatment are more likely to be conservative, Republican and to think current levels of inequality are not too large.

[23] Note that if they had simply chosen randomly, estimates for this group would be at -or at least closer to- 0 than for supporters of progressive taxes, neither of which is true.

[24] For results see figures 15 and 16 in the Appendix.

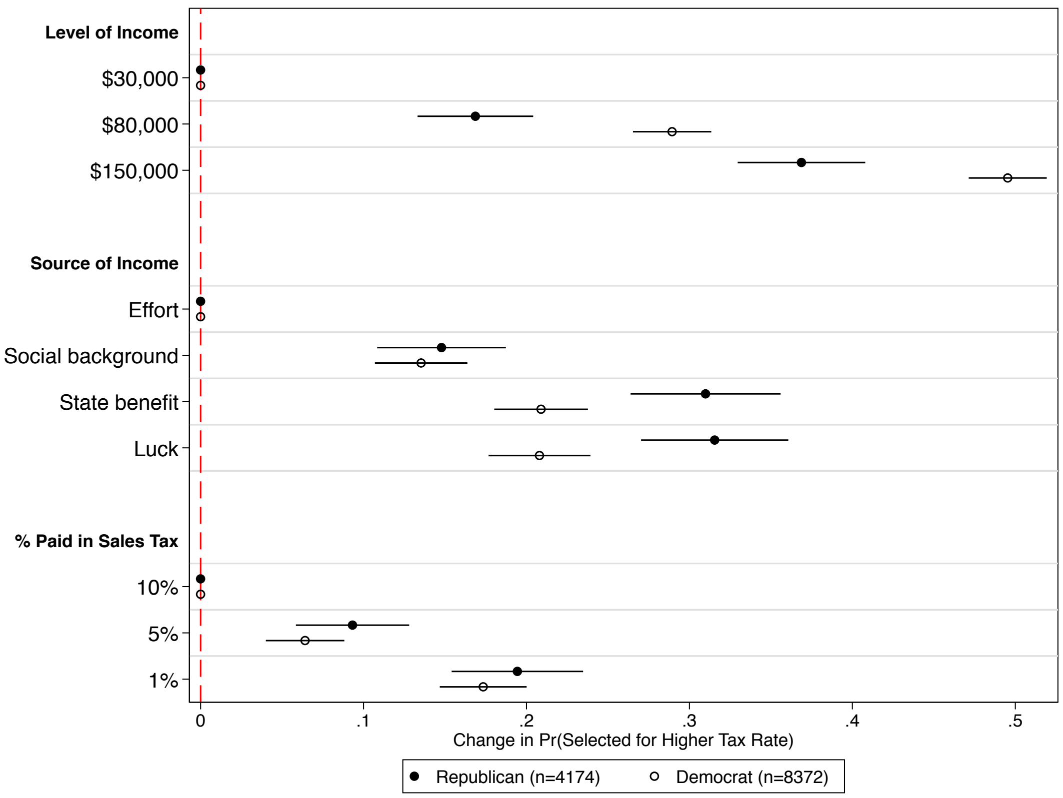
Figure 5: Effect of Profile Attributes by Respondent Adherence to Equal Treatment



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those who think everyone should pay the same share of their income in taxes, and those who think some people should pay more than others. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

In terms of race, results indicate that white respondents care less about level of income (or ability to pay) than non-white respondents, and this is not simply an expression of self-interest, as race is not correlated with income in the sample. In terms of gender, the effect of luck as a source of income is significantly larger among women (7 percentage points higher), which is consistent with previous research finding that fairness considerations vary by gender (Durante et al., 2014; Fisman et al., 2017) and that women have more redistributive preferences than men (Krawczyk, 2010; Alesina and Giuliano, 2009). Additionally, females are 6 percentage points less likely to choose profiles who have only paid 1% of their income in sales tax. It is worth noting that this is the only distinction found in the data expressing a relative[25] disagreement regarding the importance of taxes paid in determining choices.

Figure 6: Effect of Profile Attributes by Respondent Party Identification



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those who identify as Republicans, and those who identify as Democrats. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

The most interesting differences however are determined by party identification. As figure 6 shows, Democrats adhere to ability to pay much more than Republicans, who in turn care more about deservingness. These differences are in line with research arguing Republicans adhere to notions of procedural fairness while Democrats

[25]Relative in the sense that both males and females agree that the share of income paid in sales taxes is important in determining their choices; their disagreement lies on how important it is.

prioritize equalizing outcomes[26] (Miles, 2014). In particular, they suggest that Republicans' preferences for less progressive taxation derive from the fact that they assume high incomes are deserved. When incomes are not deserved though, (i.e., when they result from luck or state benefit), they do support an unequal distribution of the tax burden[27]. Furthermore, these results are robust to dividing the sample by vote choice in the 2016 presidential elections (Trump vs Clinton voters) or by ideology (conservatives vs liberals)[28], suggesting they express a deep ideological divide in fairness conceptions. This fairness or values-based explanation for conservatives' opposition to redistributive taxes complements more established views which focus on voters' ignorance (Bartels, 2005), partisan bias (Bartels, 2008), and/or misrepresentation (Page and Jacobs, 2009) in a political system more attuned to the interests of the rich (Gilens and Page, 2014; Gilens, 2012). Moreover, it is in line with Piketty's broad argument that "the main difference between voters is not their differing interests and objective functions but rather the information and ideas about policies that they have been exposed to during their social life" (Piketty, 1995, p. 578) and the differing beliefs they engender regarding the role of effort as a determinant of success.

Finally, figure 7 presents the effects of source of income and share of income paid in sales tax broken down by the level of income in the profile, to show potential interactions between attributes. As we can see, level of income accentuates the effect of every other attribute in a monotonic manner. Nonetheless, all attribute values are significant even when accompanied by the lowest level of income, suggesting their effect is not simply a consequence of income level.

The effect of social background stands out as the only one that significantly increases with income level (by 6 percentage points). The overall probability of selecting a profile with this source of income increases from 22% when income level is \$30,000 (with a baseline of 12%) to 70% when it is \$150,000 (with a baseline of 54%), suggesting that for this source of income the magnitude of the benefit one receives from one's family is of particular importance. Furthermore, despite the fact that its effect on the probability of selection is typically smaller than that of other sources of income, social background is also striking because -similarly to share of income paid in sales tax- it does not exhibit any significant differences between groups. This suggests there is a certain consensus regarding the fact that income resulting from

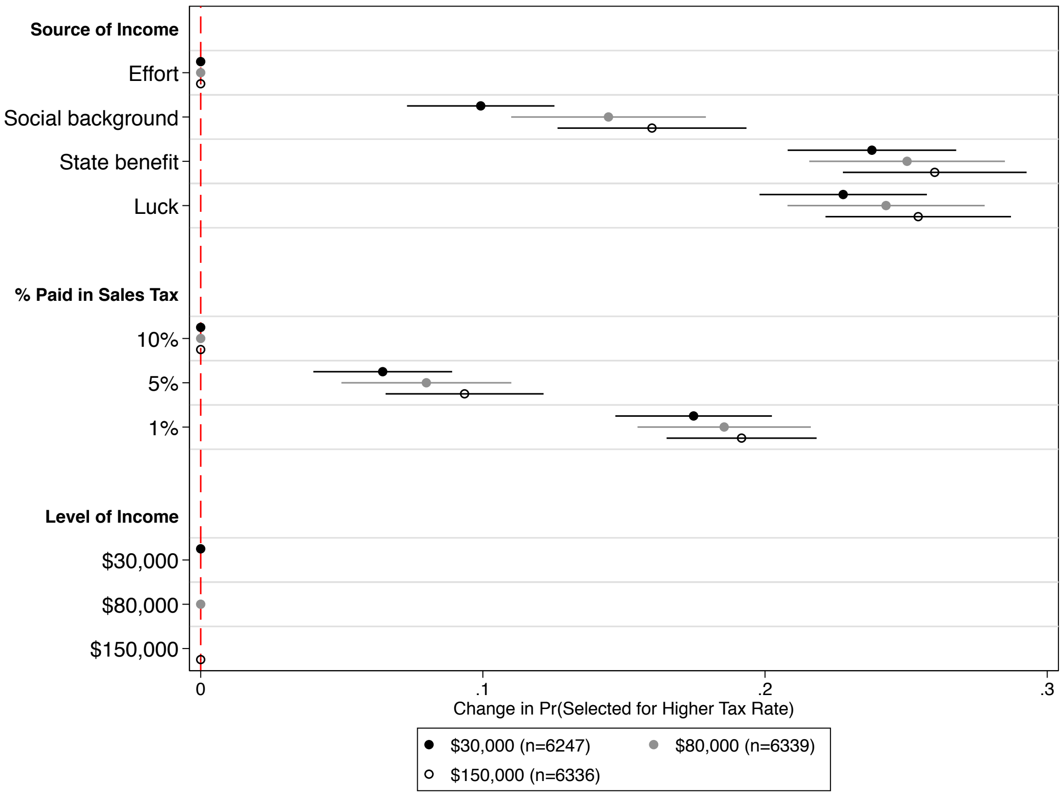
[26]Moreover, these differences are not simply an expression of self-interest, as income is not highly correlated with party identification or ideology in the sample (Spearman's ρ=0.10 and 0.11, respectively).

[27]This is also in line with Di Tella et al. (2017), who argue Republicans are unwilling to redistribute because they have a high opinion of the rich. However, when they think the rich are corrupt they do support raising their taxes (providing additional evidence of the relevance of source of income).

[28]For results see figures 27 and 28 in the Appendix.

one's social background deserves to be taxed at a higher rate, particularly when it is considerable. Further research should examine the extent to which these findings are robust to different specifications of social background and could be used to mobilize support for estate taxes[29].

Figure 7: Effect of Profile Attributes by Level of Income in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of profiles: those with income level $30,000, those with income level $80,000 and those with income level $150,000. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

No other significant interactions between attributes were found. See the Appendix for results.

[29]However, the formative study did reveal that respondents perceived receiving an inheritance as a result of both social background and luck, which might indicate estate taxes may be subject to the same disagreements as income resulting from luck.

4 Robustness Tests

In addition to the main analyses reported here, I conducted a series of diagnostic and robustness tests, results for which are found in section A.4 of the Appendix. Diagnostic tests, based on Hainmueller et al. (2014), were intended to check that two basic conjoint analysis assumptions hold: stability and no carryover effects, and no profile order effects. The first was assessed by testing whether AMCEs were similar across the five tasks; the second by testing whether they were similar across the two profiles in each task. In order to address potential external validity concerns, I also checked for the existence of row-order and atypical profile effects. The first was intended to assess whether respondents suffered from primacy or recency effects by testing whether AMCEs were similar regardless of the row in which attributes appeared[30]. The second was intended to assess whether respondents reacted differently to profiles that might be considered atypical, such as the ones combining winning the lottery or owning a business bailed out by the government and an annual income of only \$30,000. The only one of these tests to return a significant effect was the last one, suggesting respondents reacted to atypical profiles by basing their choices more on the level of income and less on the source of income. To ensure this does not drive my results, I repeated all analyses excluding choices involving atypical profiles (see Appendix section A.6). The main patterns in the results remain, but significance levels are affected by the loss in power resulting from a smaller sample size.

I also conducted two tests intended to examine whether results were affected by respondents' attention level. First, I included an attention screener[31] in the survey, after 3 of the 5 conjoint tasks had been conducted. Only 2% of respondents failed the screener, and therefore excluding them from the analysis does not change results. Second, I compare AMCEs for respondents who completed the survey below and above the median time, but do not find any significant differences (although those who took less time seem to choose based on income level to a greater extent, suggesting there may be some degree of satisficing going on).

To ensure results are not driven by respondents who participated in the formative study and may interpret the sources of income used in the survey differently[32], I

[30]This test was possible because the order in which the attributes appeared in the conjoint table was randomized between subjects.

[31]Following Bechtel and Scheve (2013), the attention test involved asking respondents the following question: "We are interested in learning about your preferences on a variety of topics, including colors. To demonstrate that you've read this much, just go ahead and select both red and green among the alternatives below, no matter what your favorite color is. Yes, ignore the question below and select both of those options. What is your favorite color?"

[32]One could also conceive of this as testing whether habitual survey respondents behave differently.

checked whether results changed if I excluded them. They did not.

Finally, since I examine whether choices vary by certain respondent characteristics in several different ways[33], I repeated the relevant analyses using multiple comparisons adjustments. Specifically, I estimated interaction models for each attribute and respondent characteristic and assessed whether choices varied across the groups determined by respondent characteristics through a joint significance test (at the 10% level). This confirmed that education and employment status do not moderate attribute effects, but inequality in place of residence, level of income and age do. For the latter, I re-estimated the interaction models using a false discovery rate (FDR) adjustment, which allows me to identify as many significant features as possible, while incurring a low proportion of false positives (namely, 5%)[34]. Specifically, I calculated q-values using the Simes procedure, which assumes a nonnegative correlation of p-values (Newson, 2010), and confirmed that differences in the effects reported in previous sections remain[35].

5 Discussion and Conclusions

While existing literature acknowledges the fact that fairness considerations play a significant role in determining peoples' preferences regarding taxation, it comes short of addressing which types of fairness considerations are used, by whom, and what their relative importance is. It is this important gap that this paper has sought to contribute to. In so doing, it endeavors to advance a richer understanding of peoples' preferences for how the tax burden should be distributed, with the goal of contributing to the development of tax policies that can enjoy widespread support.

The conjoint experiment presented here has produced direct evidence that people use ability to pay, deservingness and compensatory fairness considerations when deciding how to distribute the tax burden. Furthermore, it also produced evidence

[33] I measured level of income in three different ways and age, education, employment status and inequality in place of residence in two different ways each (see results in the Appendix for operationalizations). Note that I consider inequality aversion and inequality in place of residence to test two different hypotheses: that general preferences for inequality determine tax preferences, and that exposure to inequality determines tax preferences.

[34] The reason I use an FDR adjustment instead of the more conservative family wise error rate is that I consider the moderator analyses performed here as mainly exploratory (in the sense that preferences regarding several attributes among different subgroups are being tested for the first time), and therefore want to allow as many effects as possible to reveal themselves.

[35] In particular, respondents living in more unequal zip codes care more about level of income than those in less unequal zipcodes, respondents with very high incomes care less about level of income and more about state benefit and luck as sources of income than those with low income, and respondents in their forties care more about state benefit and luck as sources of income than those in their twenties. See tables 2-16 in section A.4 of the Appendix for results.

consistent with equal treatment, inequality aversion and self-interest playing a role in determining tax preferences. However, the effects of these other sources of preferences were never large enough to offset the influence of the fairness considerations on which I focused, and instead acted to moderate their effects.

Subgroup analyses reveal important and systematic differences in the fairness considerations used by different subsets of respondents. Perhaps the most important of these differences is the one separating conservatives and liberals (or Republicans and Democrats), with the former giving more importance to sources of income (or deservingness) and the latter to levels of income (or ability to pay). This distribution of preferences is consistent with the notion that ideological divisions are based on deep-rooted differences in conceptions of justice, with conservatives placing more emphasis on the fairness of procedures, and liberals on that of outcomes. The practical implication of this is that conservative opposition to redistribution is conditional on the assumption that income or wealth were earned fairly, when evidence exists that this is not the case, support for progressive taxation is expressed.

In terms of the relative importance of different fairness considerations, results indicate ability to pay can have the largest effect on the probability that a profile will be selected for the higher tax rate (when income is relatively high), substantiating policy-makers' focus on level of income. Nonetheless, deservingness and compensatory considerations can also have a substantial effect, -and one that is less prone to political dissent-. In particular, state benefit and luck as sources of income, and 1% of income paid in sales taxes all have an equally large overall probability of selection (around 60%). The role played by these fairness considerations is thus highly conditional on the specific attribute levels they are attached to.

Another important contribution of this paper lies in the fact that it presents the first test of the influence of compensatory arguments on tax preferences, allowing for a richer understanding of peoples' conceptions of deservingness and fairness in taxation. In this regard, I find that compensatory arguments play an important role, regardless of whether they are interpreted as compensation for the receipt of a bailout or for the regressivity of consumption taxes. Moreover, the large effect of receiving a state benefit suggests research on deservingness would profit from expanding upon its almost exclusive focus on the distinction between effort and luck.

In terms of policy, two alternatives to the current focus on income levels are brought to the fore. The effects of both the share of income paid in sales taxes and income resulting from social background exhibited the peculiarity of averting any political disagreements. This suggests they may be used to garner widespread support for more progressive tax systems. In particular, the effect of the share of income paid in sales taxes indicates compensatory arguments could be a powerful instrument for policy change, given that respondents express a strong rejection of the fact that rich people pay a lower share of their income than poor people.

When combined with previous findings, these results suggest that while inequality itself may not be a sufficient reason to support more progressive taxes (Kuziemko et al., 2015), the unfairness of unequal outcomes may be. That is, if the rich are shown to not deserve their wealth, either because they are corrupt (Di Tella et al., 2017), or because they have unfairly benefited from the state's action, or because they pay less of it through indirect taxes, then support for redistribution increases. People -conservatives, in particular- oppose government intervention to redistribute what they perceive as hard-earned income, but may approve of it if it punishes unfair advantages. In fact, respondents' reactions to the state benefit source of income indicate fairness preferences in taxation not only involve rewarding effort but also using taxes as a punishment for behavior that is considered inequitable or corrupt (as in the case of Di Tella et al. (2017)).

Nonetheless, these initial findings need to be validated and in particular, the robustness of these results to the particular sources of income used needs to be assessed. Even though the sources of income resulted from a formative study that sought to ensure they were interpreted in the way intended, answers to the open ended justification question reveal they may still be subject to some confounding. Thus, the "Started own small business" cue, intended to be interpreted as evidence of effort, seems to have also primed cultural evaluations of small business owners as job creators contributing to the well-being of their communities. This means profiles including this source of income seem to have been less likely to be selected both because income was well deserved, and because of the indirect benefits they provide to the community. If that is so, then the effects of the other sources of income may be somewhat overstated. Similarly, the "Owns business that was bailed out by the government" cue seems to have generated very negative feelings and it is not clear the extent to which these are due to negative perceptions of state benefits in general or of this particular type of state benefit.

Responses to the "Receives annuity from lottery prize" cue called attention to the fact that respondents also take into account the stability of the source of income when deciding who to chose for the higher rate, a factor that is not usually considered in this literature. A small number of respondents interpreted this source of income as a one time thing and were therefore reluctant to select a profile on its basis.

Given the well-studied differences in the role of deservingness considerations in the US and Europe, an interesting extension to this research would be to replicate it in different countries in order to compare how fairness considerations vary between cultures. Moreover, in line with recent findings in the literature regarding the moderating effect of trust in government on preferences for taxation and redistribution

(Kuziemko et al., 2015; Di Tella et al., 2017), cross-country analysis could also prove profitable from that perspective. Finally, given the strong effect of luck on preferences, it would be interesting to assess whether bad luck has symmetrical effects, leading to preferences for lower -or even negative- taxes, linking this research to the extensive literature on social insurance.

A Appendix

A.1 Formative Study

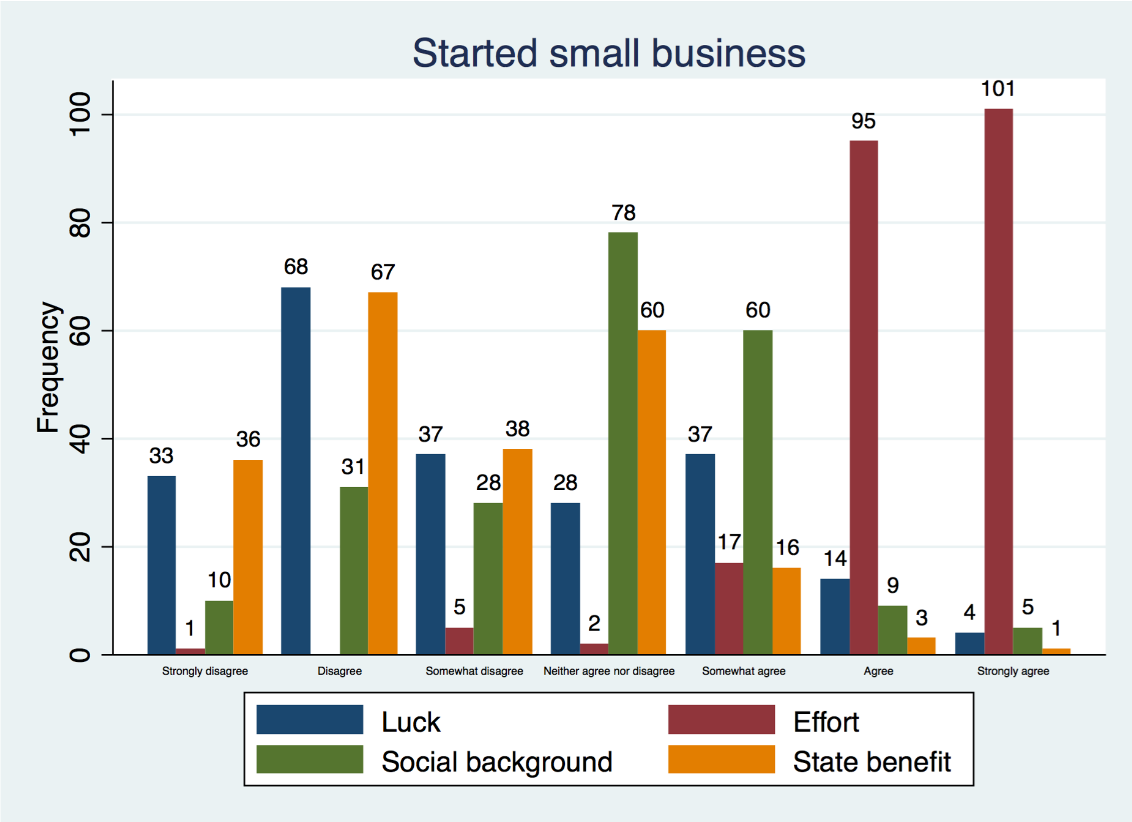
As reported in the paper, a formative study was conducted in order to identify the sources of income to use in the experiment. The goal was to find sources of income that i) would be interpreted as the product of effort, social background, state benefit and luck, respectively; ii) were relatively orthogonal to one another; and iii) were independent of level of income.

In this study, samples of 250 MTurk respondents were presented with different sources of incomes and were asked to express their agreement with the statement that each source of income resulted from luck, effort, state benefit and social background on a 7-point likert scale.

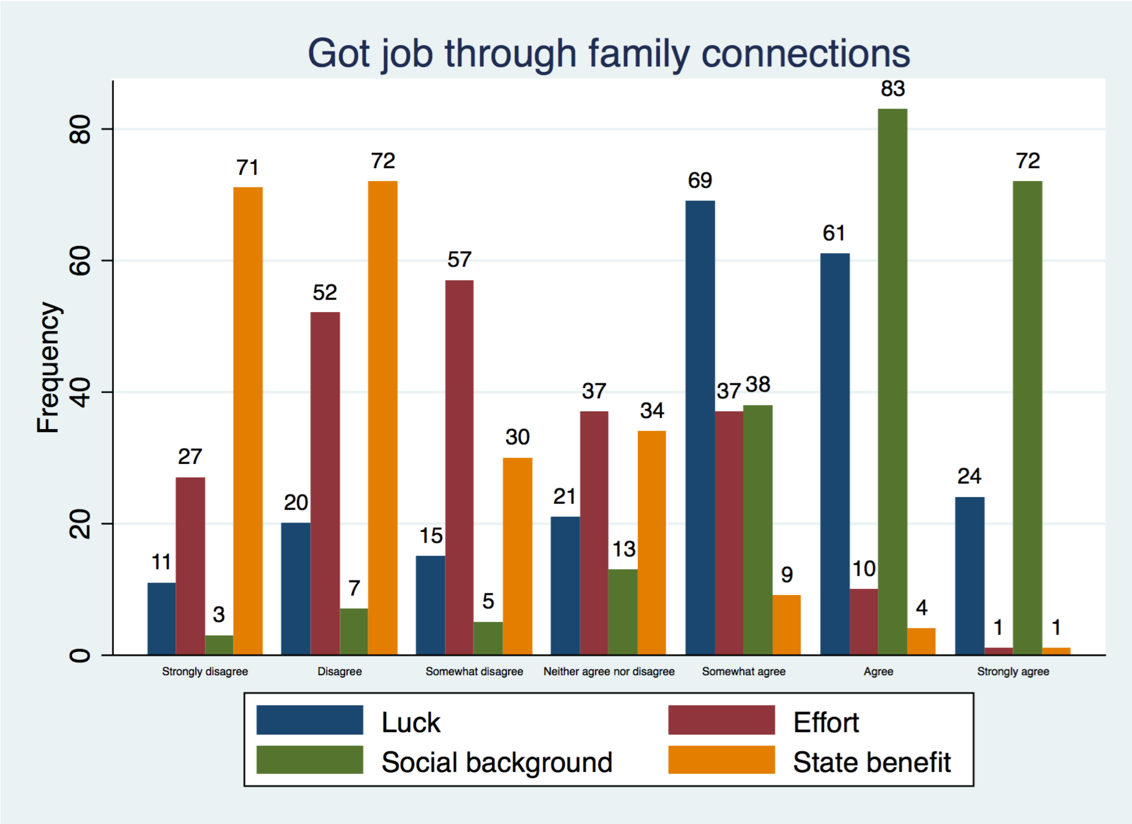
The sources of income tested were:

- Is a construction worker.
- Got trained as an engineer and a found a job.
- Started his own small business.
- Owns a business that gets state contracts through lobbying.
- Owns a company that has provided services to the state as a defense contractor.
- Owns a dairy farm that benefits from special legislation.
- Owns a bank that was bailed out by the government.
- Owns a business that was bailed out by the government.
- Owns a business that gets state contracts through his political connections.
- Works in the family business.
- Has a trust fund.
- Got a job through family connections.
- Received an inheritance.
- Receives an annuity from a lottery prize.

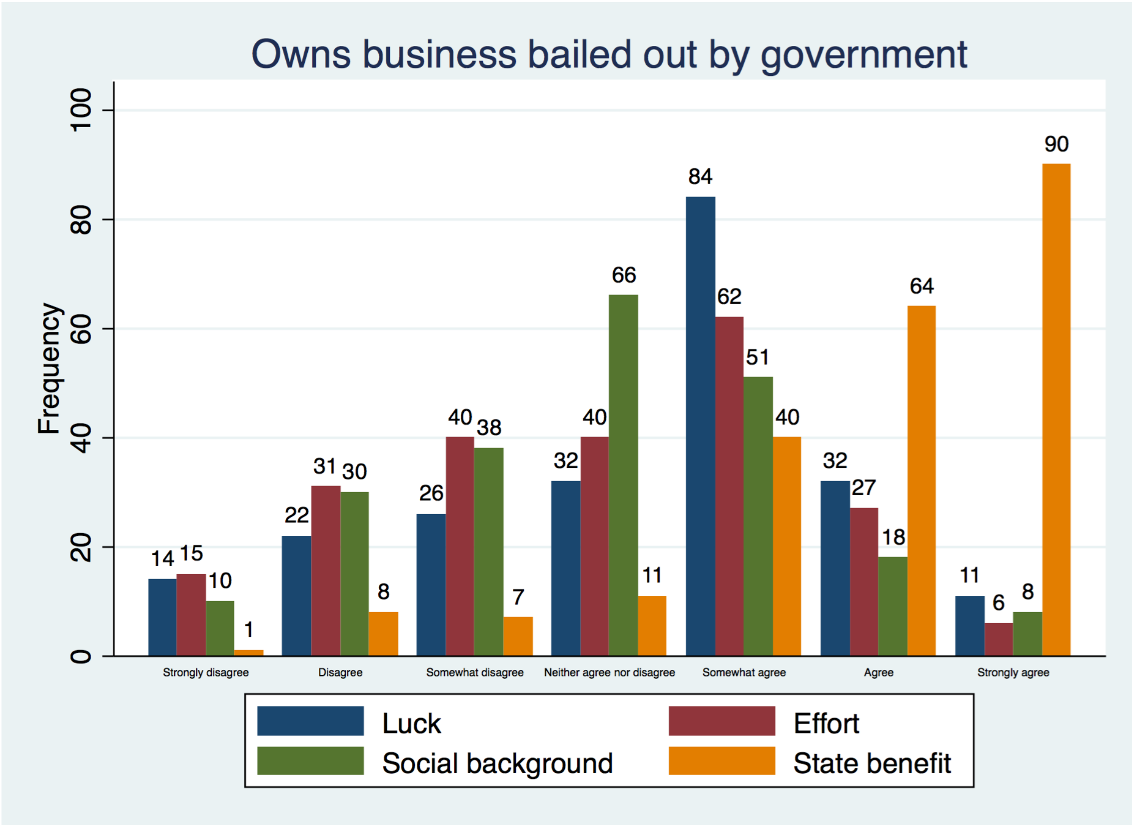
Results for the sources of income selected are included below.



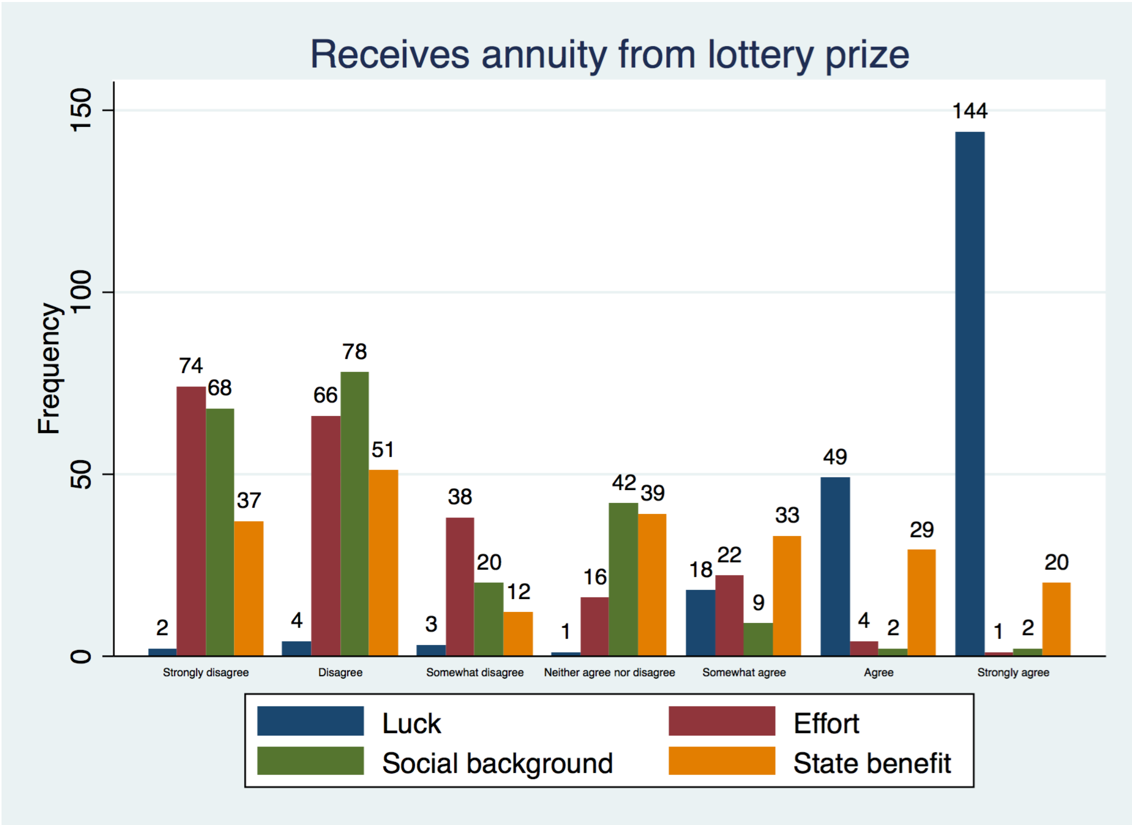
Note: Histogram of survey responses. Numbers indicate the distribution of 221 respondents across response options for each source of income. The fastest 15% of responses were excluded.



Note: Histogram of survey responses. Numbers indicate the distribution of 221 respondents across response options for each source of income. The fastest 15% of responses were excluded.



Note: Histogram of survey responses. Numbers indicate the distribution of 221 respondents across response options for each source of income. The fastest 15% of responses were excluded.



Note: Histogram of survey responses. Numbers indicate the distribution of 221 respondents across response options for each source of income. The fastest 15% of responses were excluded.

A.2 Sample and Weights

As stated in the paper, the survey was conducted on a sample of 2,000 MTurk respondents. The task was published in four batches between the 17th and 18th of October 2017, with the condition that respondents could not participate more than once. The first two batches, of 500 and 1,000 respondents had the restriction that only workers located in the US and with an approval rate of 90% could participate. The last two batches, of 300 and 200 respondents, had the additional restriction that respondents had to have annual incomes above $100,000 and below $25,000, respectively. This was done with two objectives. The first was to ensure sufficient power for analyses involving splitting the sample by income (testing for the presence of self-interest). The second was to make sure representative population weights could be constructed without having to rely on a small number of observations of underrepresented high and low income respondents.

Once the sample was ready, entropy balancing weights were constructed to adjust the sample to the margins of the adult population on age, gender, education, race, household income, partisanship and census region. Table 3 presents the distribution of socio-demographics in the raw sample, the weighted sample, and the population. Weights range between 1 and 15.

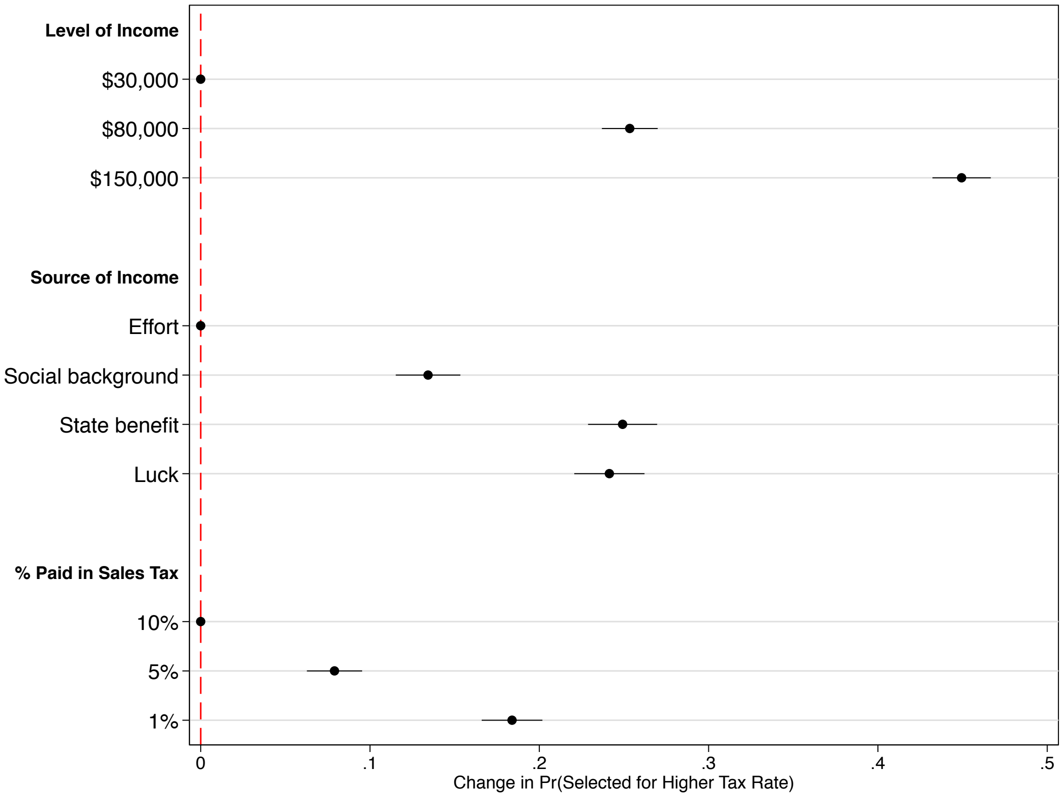
Table 3: Distribution of Socio-Demographics

Group	Raw Sample	Weighted Sample	Population
Gender: Male	.50	.49	.49
Race: White	.79	.78	.78
Age: 18-29	.29	.21	.21
Age: 30-49	.55	.34	.34
Age: 50+	.17	.45	.45
Education: Some college or less	.33	.60	.60
Education: College graduate	.51	.29	.29
Education: Post-graduate	.16	.11	.11
HH Income: $9,999 or less	.06	.05	.05
HH Income: $10,000-$19,999	.09	.07	.07
HH Income: $20,000-$29,999	.11	.08	.08
HH Income: $30,000-$39,999	.10	.09	.09
HH Income: $40,000-$49,999	.09	.08	.08
HH Income: $50,000-$79,999	.20	.21	.21
HH Income: $80,000-$99,999	.09	.11	.11
HH Income: $100,000+	.25	.32	.32
Region: Northeast	.20	.18	.18
Region: Midwest	.21	.21	.21
Region: South	.40	.38	.38
Region: West	.19	.23	.24
Party ID: Democrat	.44	.35	.35
Party ID: Republican	.22	.28	.28

NOTES. Population data comes from the 2016 Current Population Survey Annual Social and Economic Supplement, except for party identification data, which comes from the 2016 ANES Time Series Study.

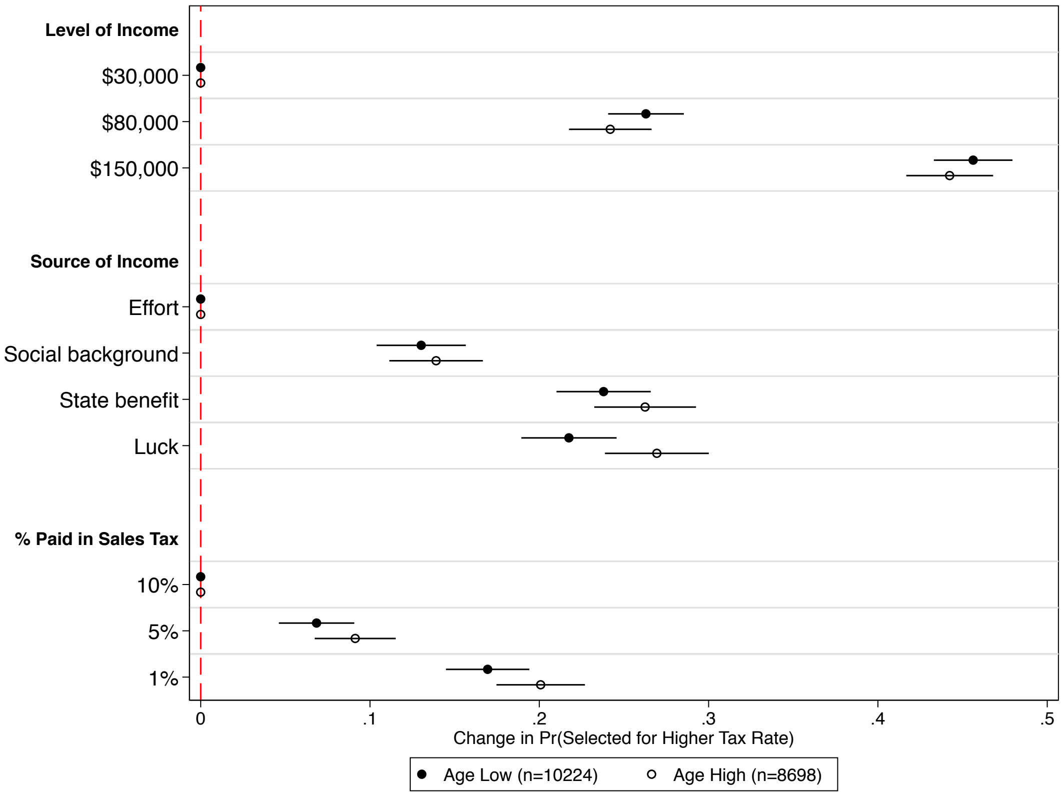
A.3 Full Results

Figure 8: Effect of Profile Attributes on Probability of Being Selected for Higher Tax Rate



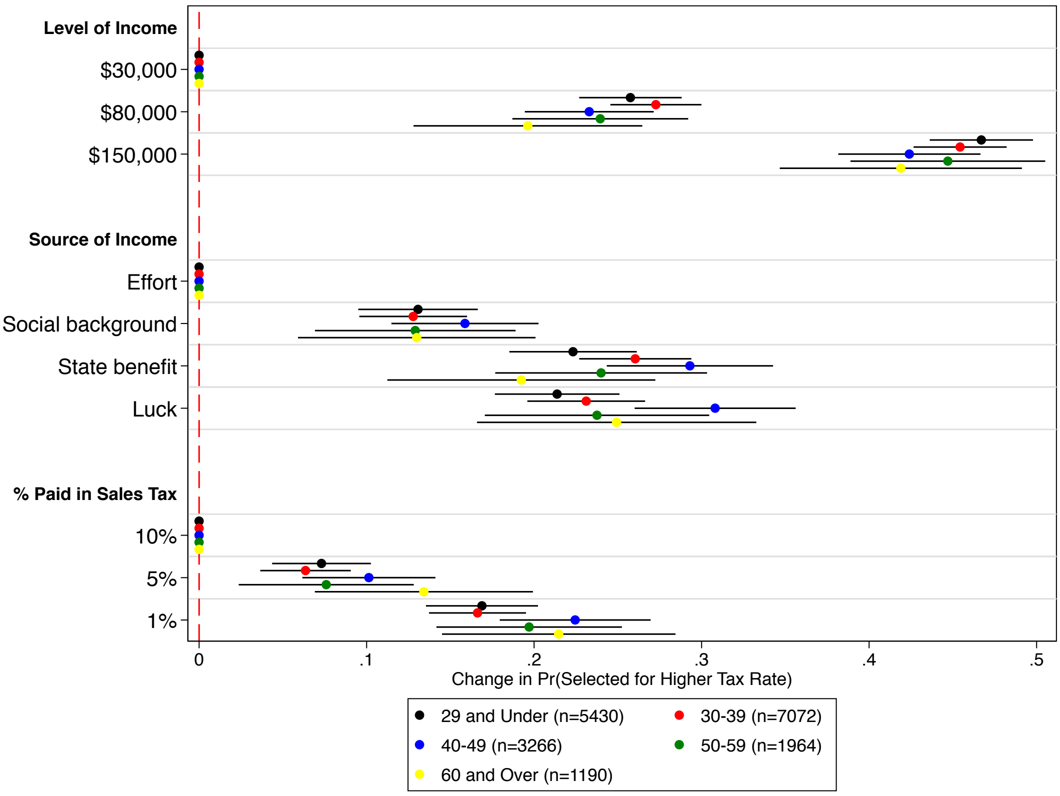
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent. Bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 9: Effect of Profile Attributes by Respondent Age



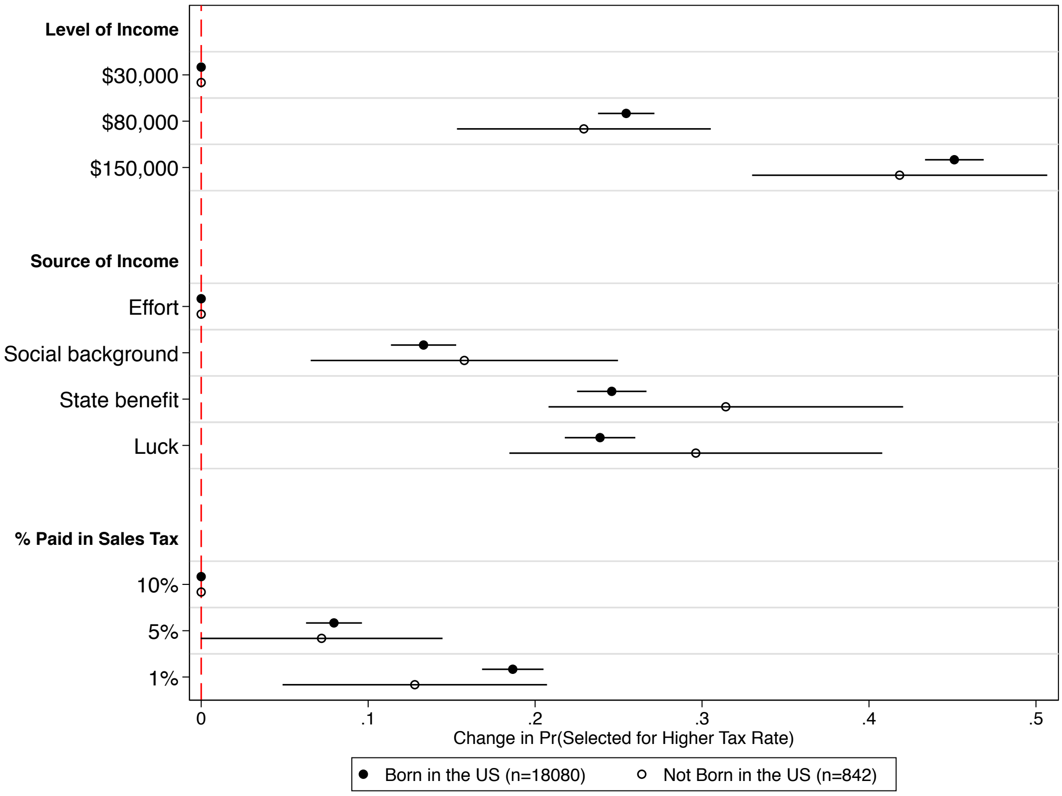
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those with age above and below the median (35). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 10: Effect of Profile Attributes by Respondent Age Groups



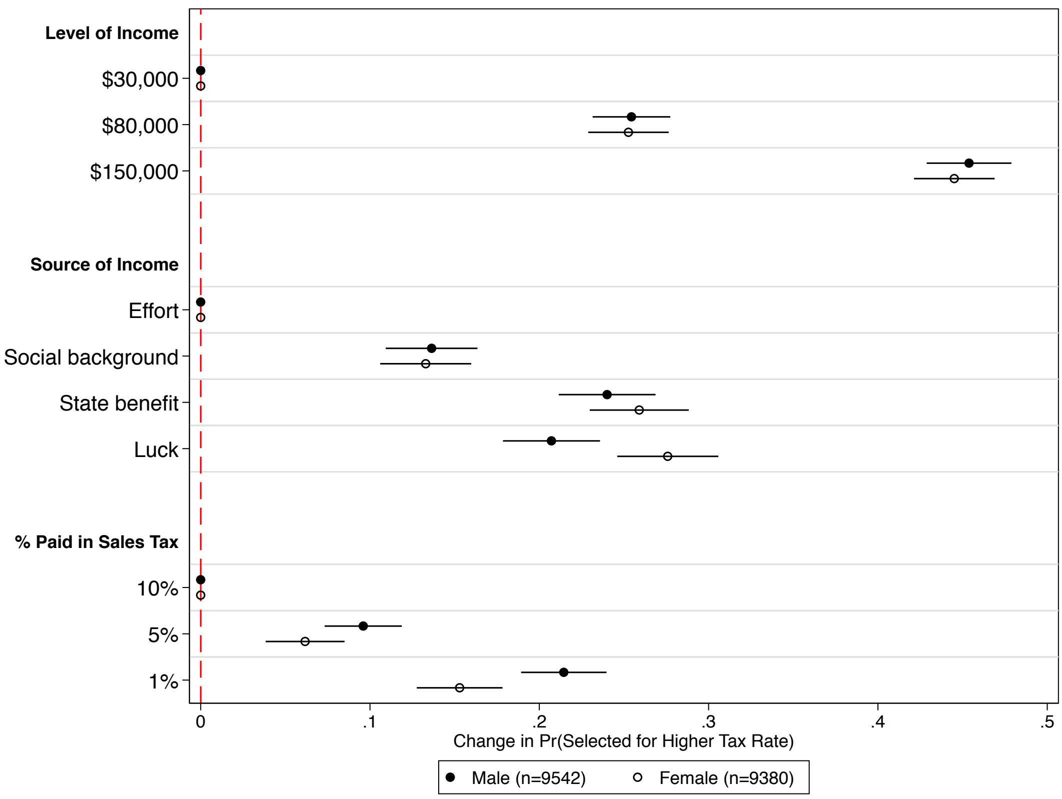
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents grouped by their age. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 11: Effect of Profile Attributes by Respondent Place of Birth



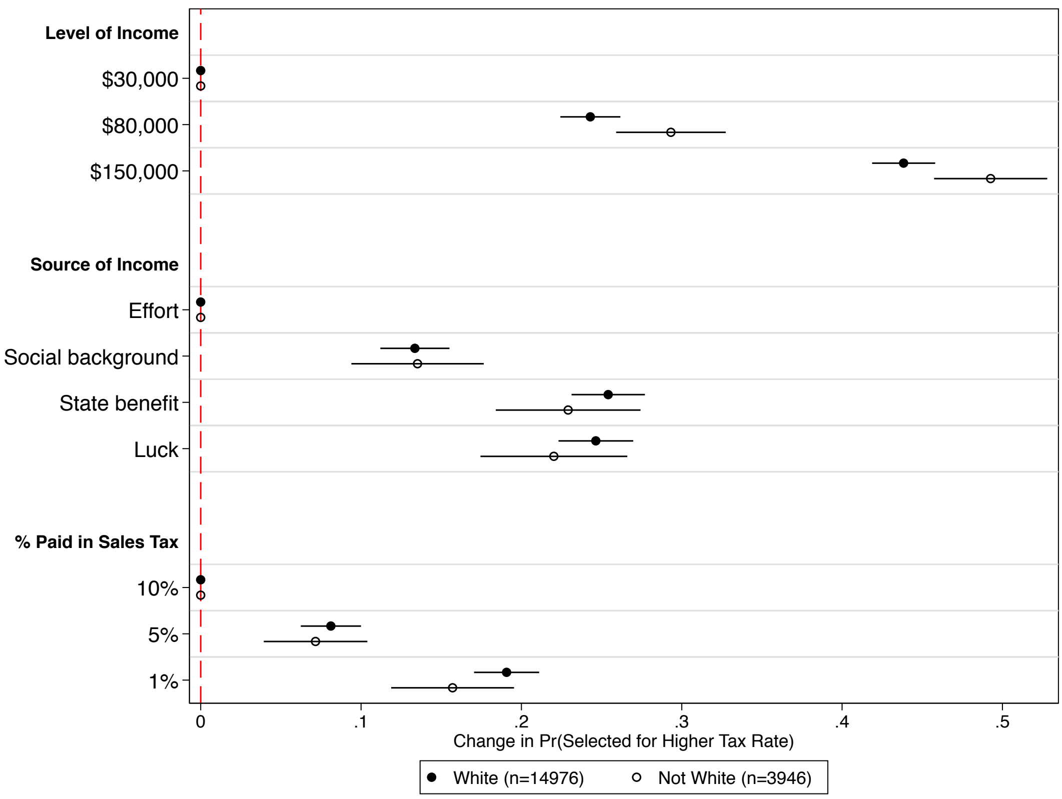
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents grouped by their place of birth. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 12: Effect of Profile Attributes by Respondent Gender



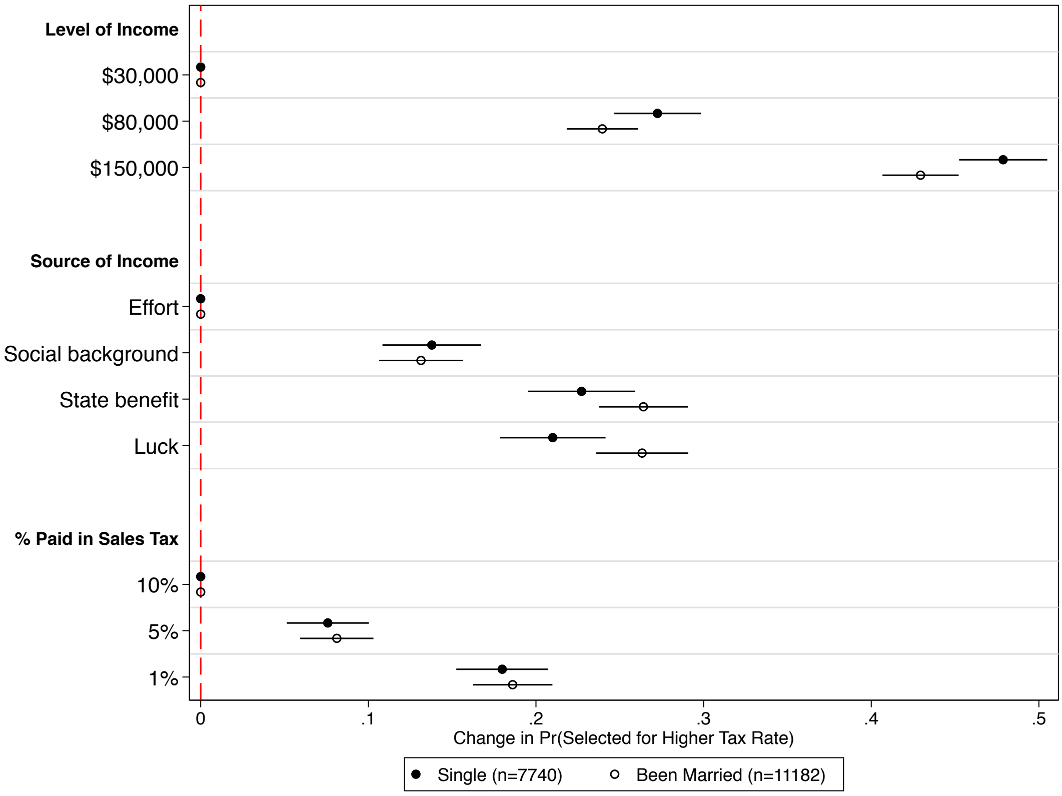
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for male and female respondents. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 13: Effect of Profile Attributes by Respondent Race



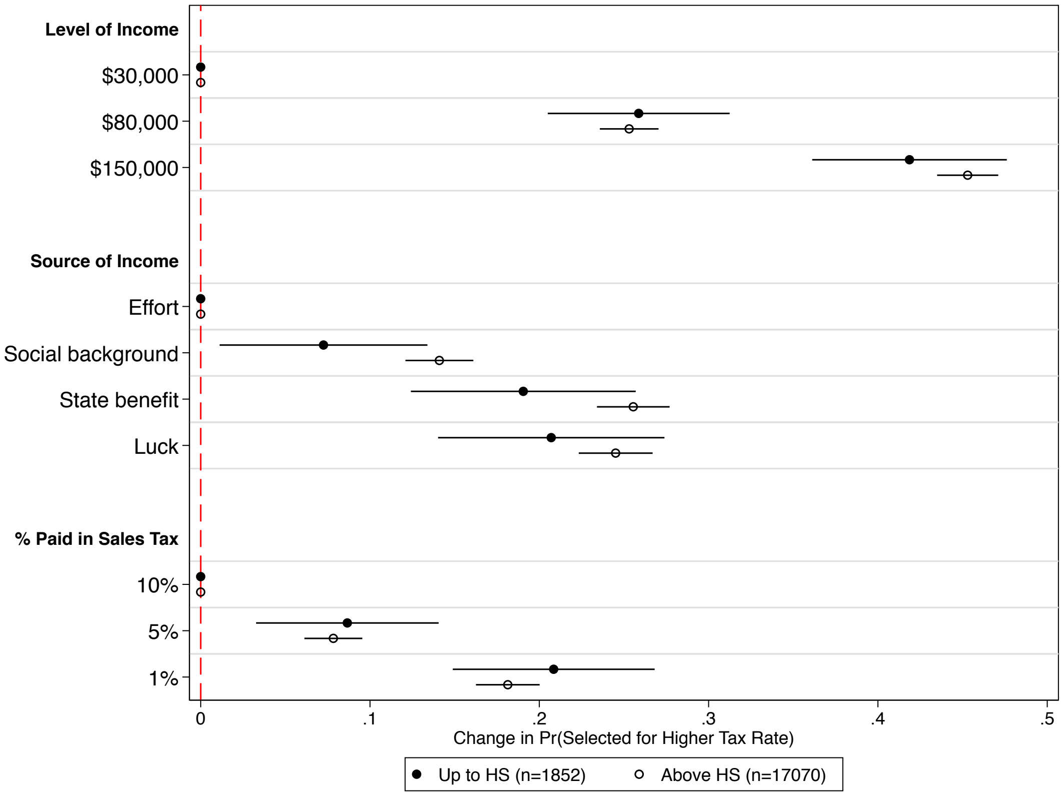
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two groups of respondents: whites and non-whites. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 14: Effect of Profile Attributes by Respondent Marital Status



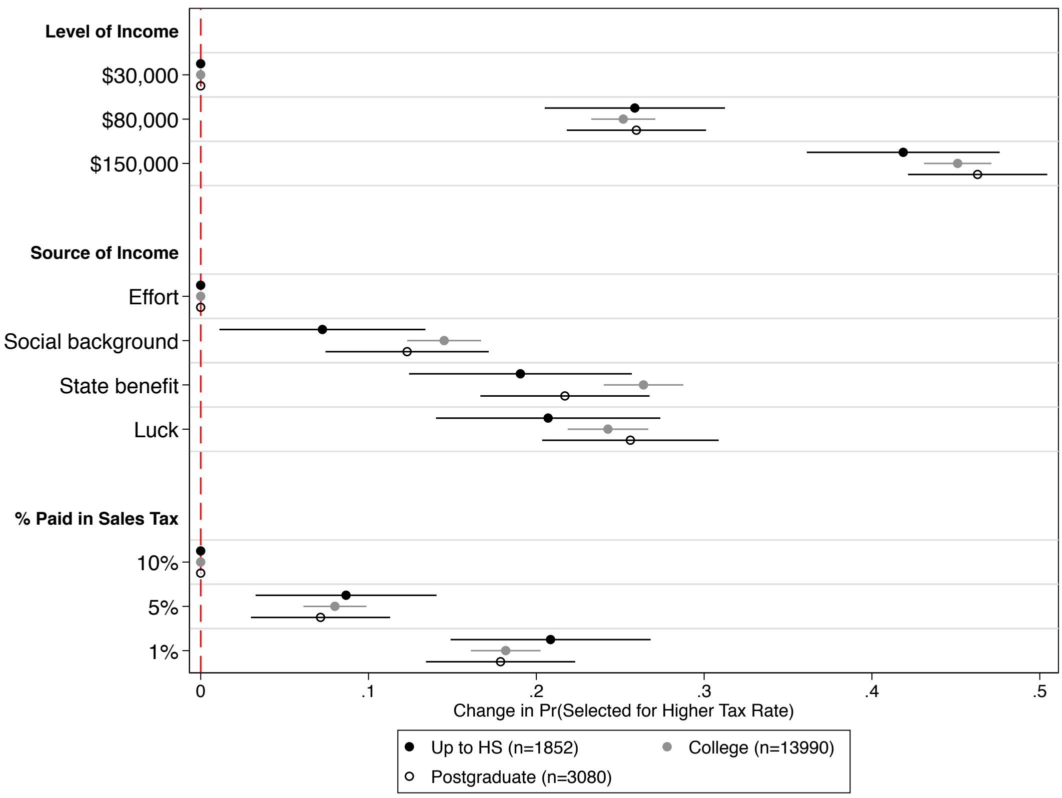
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two groups of respondents: those who are single and those who are or have been married. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 15: Effect of Profile Attributes by Respondent Level of Education: Low-High



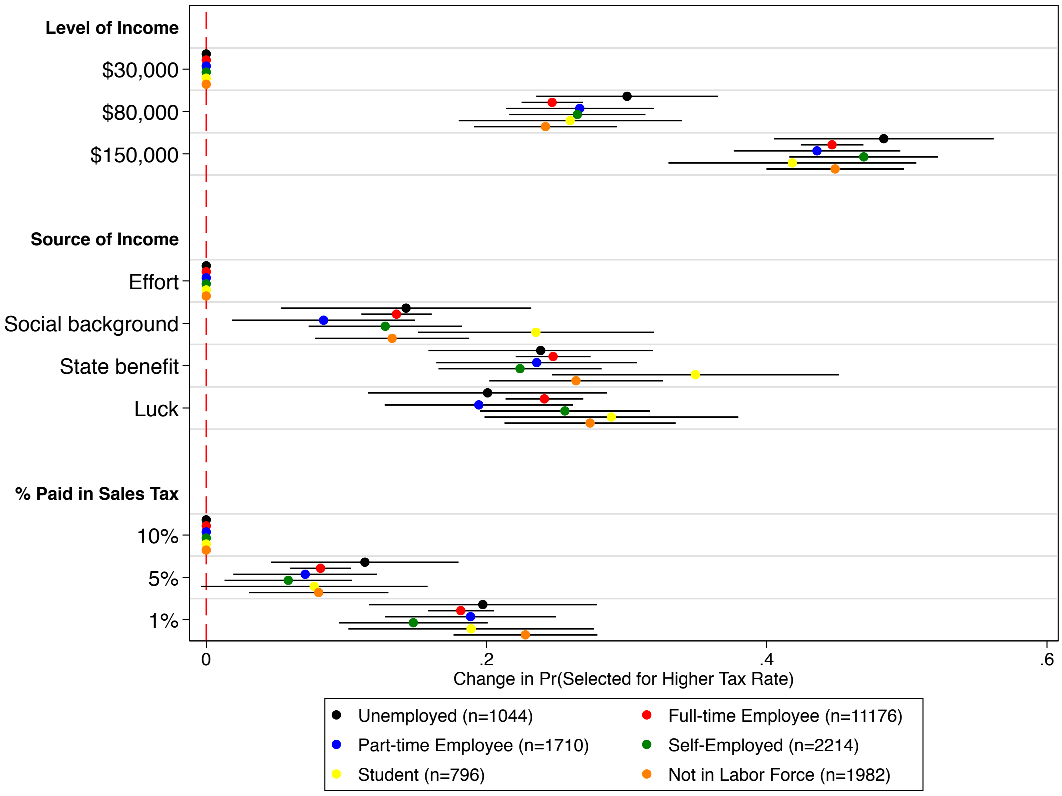
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those with education up to high school and those with education above high school. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 16: Effect of Profile Attributes by Respondent Level of Education: Low-Medium-High



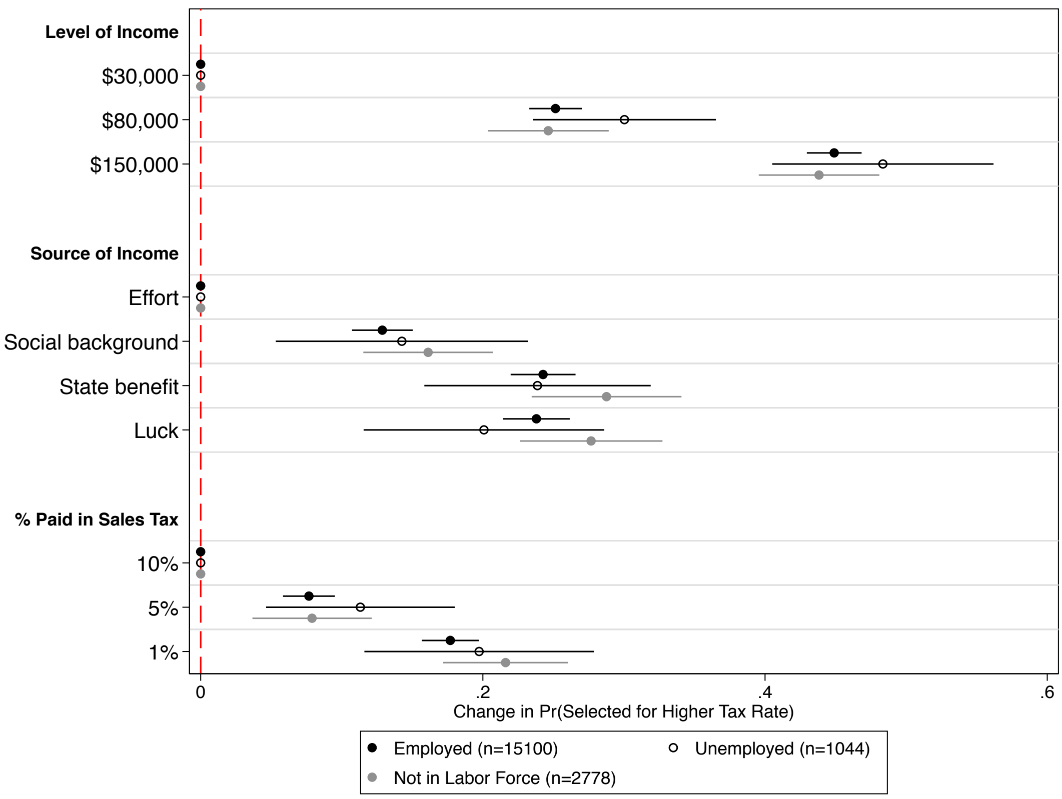
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of respondents: those with education up to high school, those with college education (at least some college, up to 4-year degree) and those with post-graduate education (MA, PhD or professional degree). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 17: Effect of Profile Attributes by Respondent Employment Status



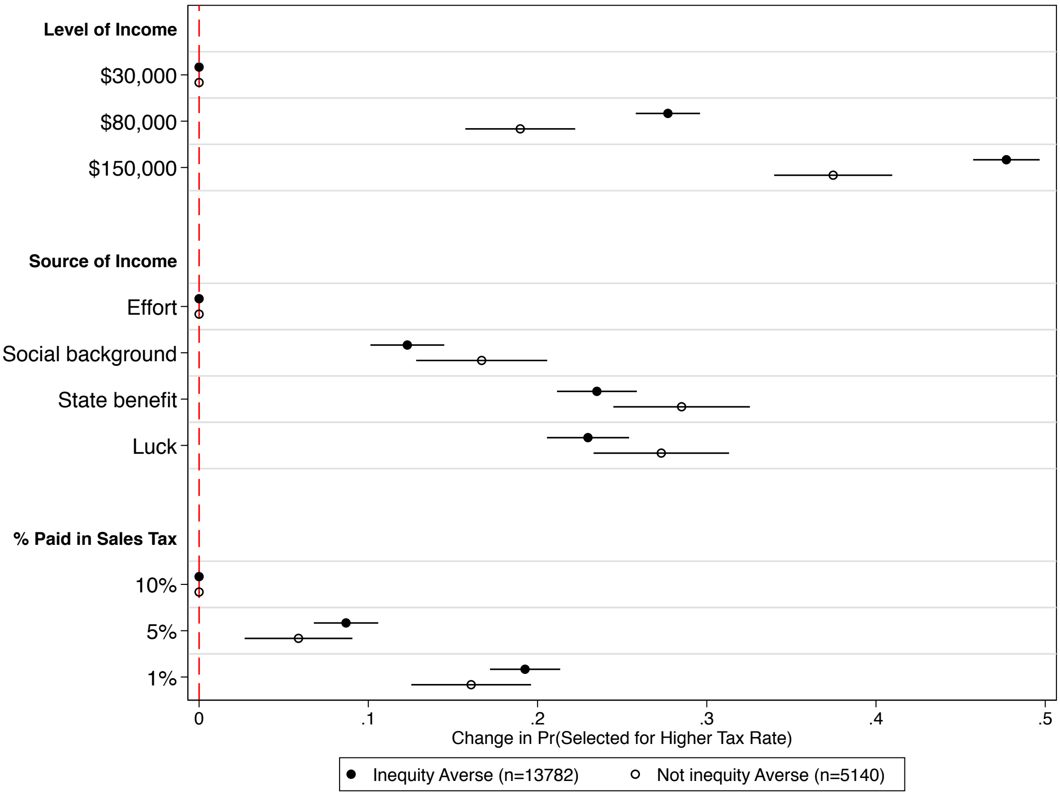
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents grouped by their employment status. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 18: Effect of Profile Attributes by Groups of Respondent Employment Status



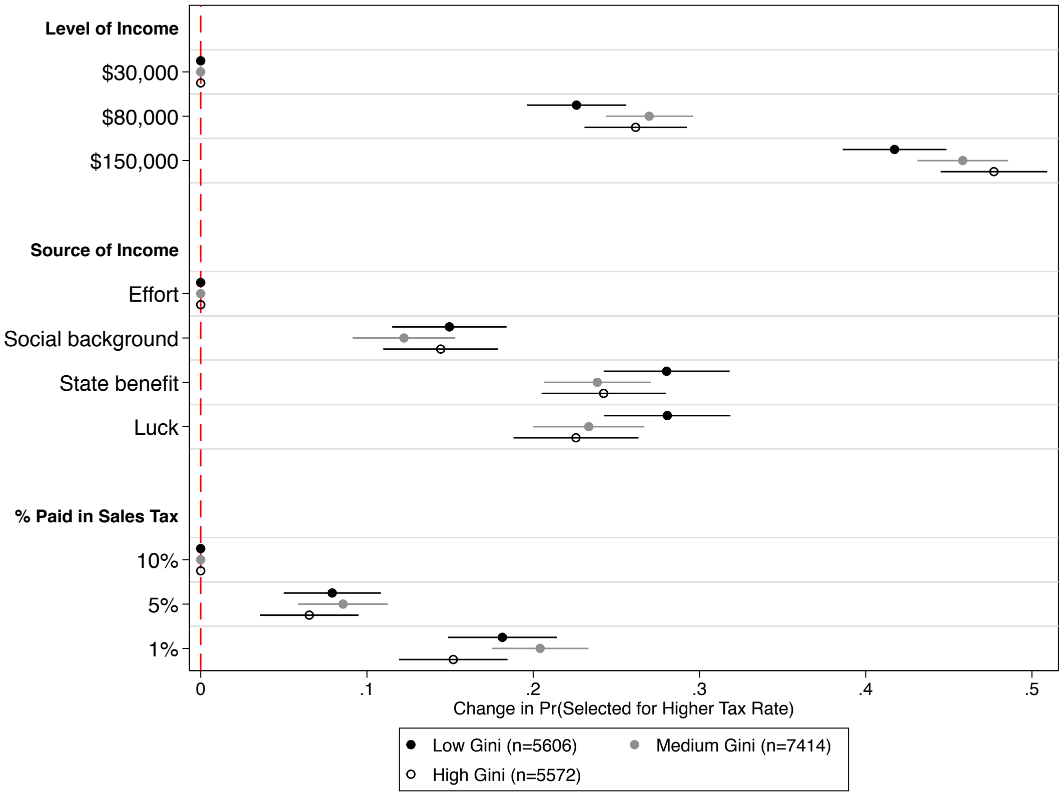
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of respondents: those employed (full, part-time or self-employed), those unemployed and those not in the labor force (including students). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 19: Effect of Profile Attributes by Respondent Inequality Aversion



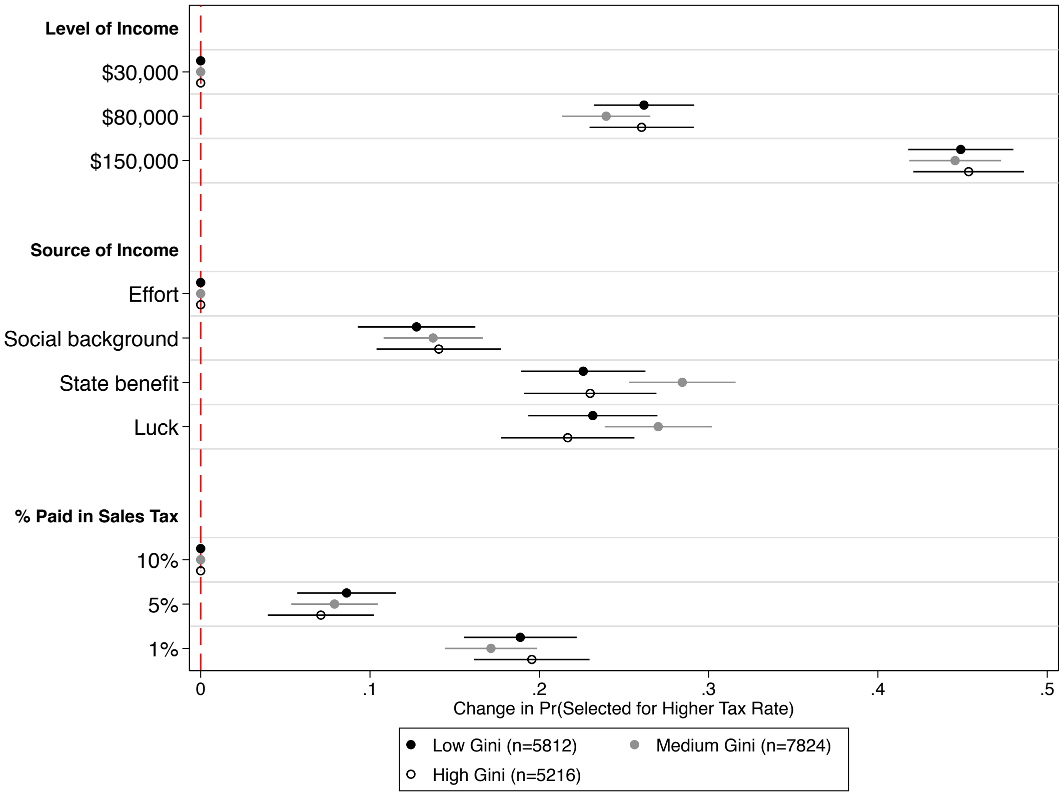
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those who think current levels of inequality are too high (inequality averse), and those who think they are either too small or about right (not inequality averse). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 20: Effect of Profile Attributes by Respondent Zip Code-Level Inequality



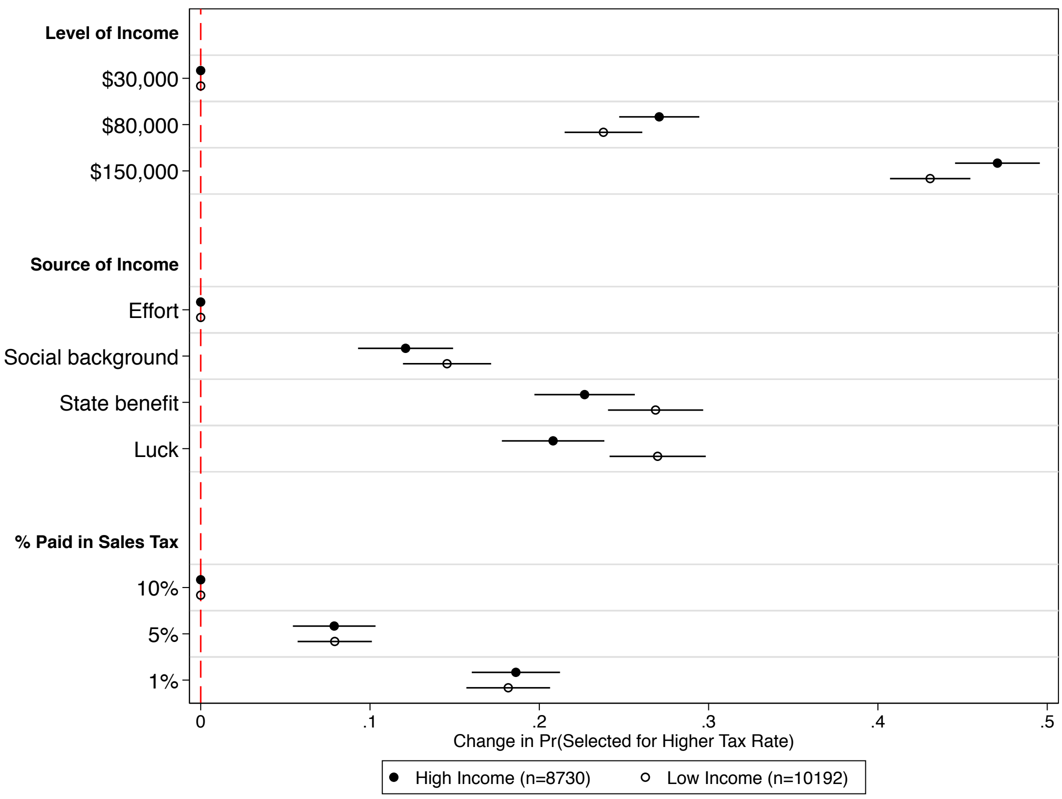
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of respondents: those living in zip codes with low (deciles 1-3 in the sample), medium (deciles 4-7) and high (deciles 8-10) levels of inequality. The points without horizontal bars denote the attribute value that is the reference category for each attribute. Zip-code level inequality data comes from the 2011-2015 American Community Survey 5-year estimates. 330 observations are missing because either zip codes were invalid (or missing), or inequality data was unavailable for them.

Figure 21: Effect of Profile Attributes by Respondent State-Level Inequality



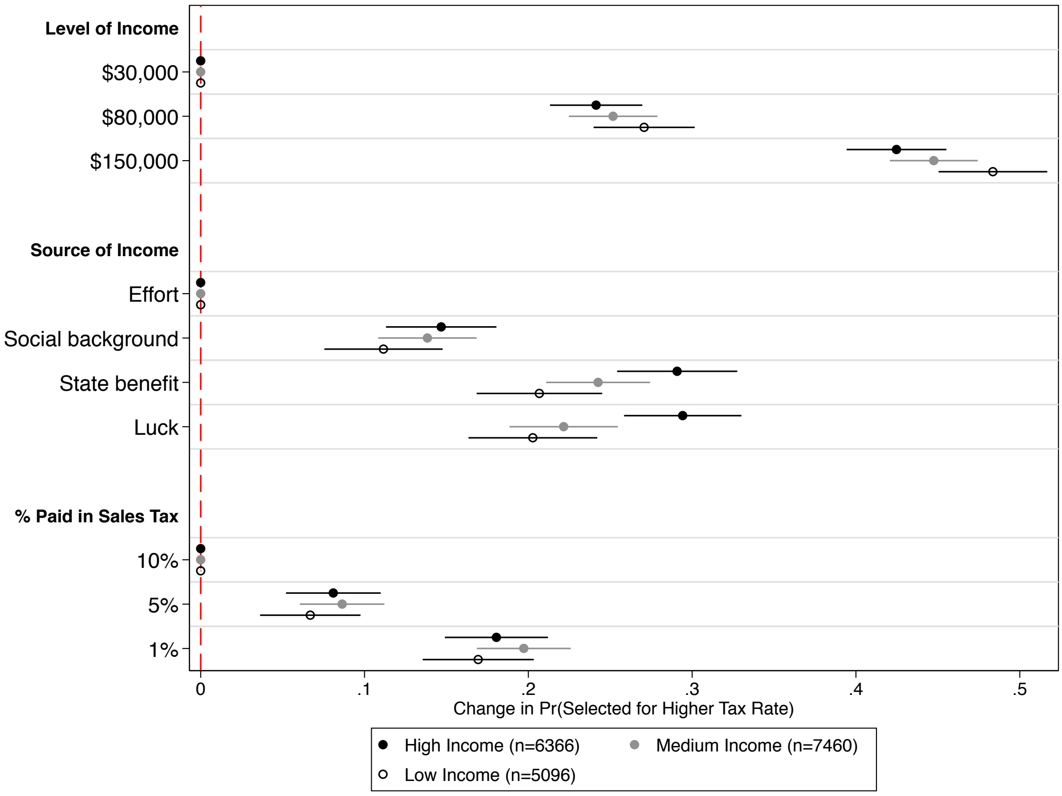
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of respondents: those living in states with low (deciles 1-3 in the sample), medium (deciles 4-7) and high (deciles 8-10) levels of inequality. The points without horizontal bars denote the attribute value that is the reference category for each attribute. State-level inequality data comes from the 2016 American Community Survey 1-year estimates. 70 observations are missing because zip codes were invalid or missing.

Figure 22: Effect of Profile Attributes by Respondent Income Level: Low-High



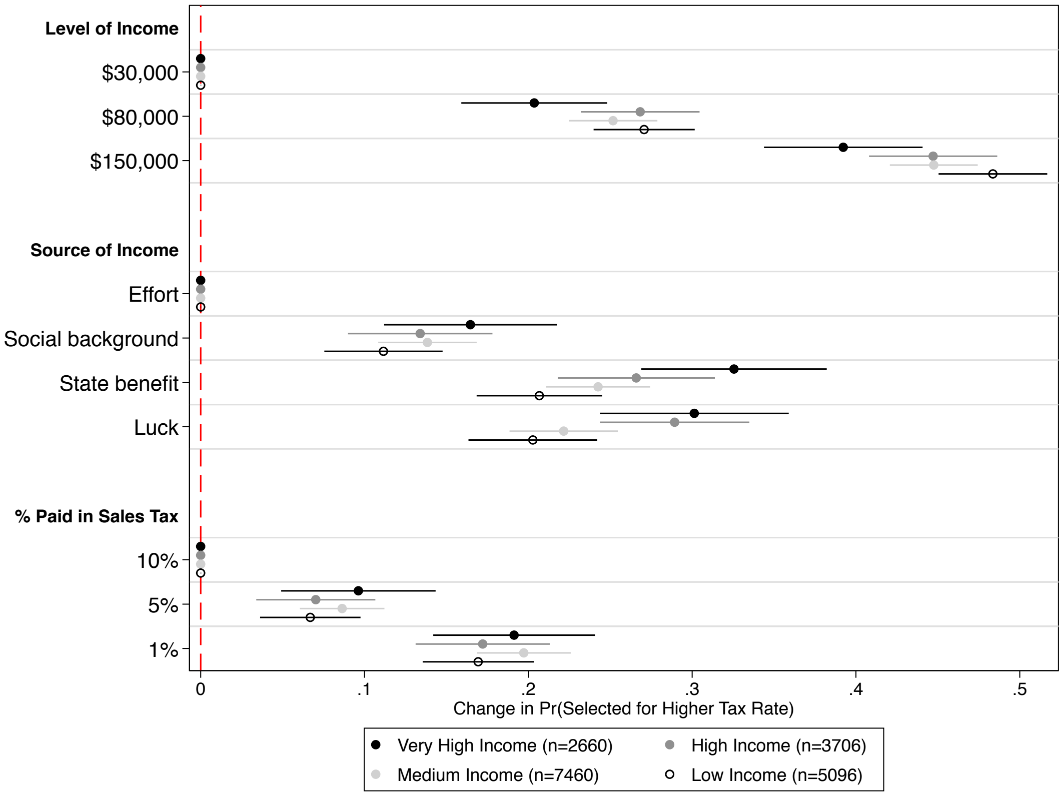
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those with annual incomes below the sample median ($50,000 to $79,999) and including and above the sample median. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 23: Effect of Profile Attributes by Respondent Income Level: Low-Medium-High



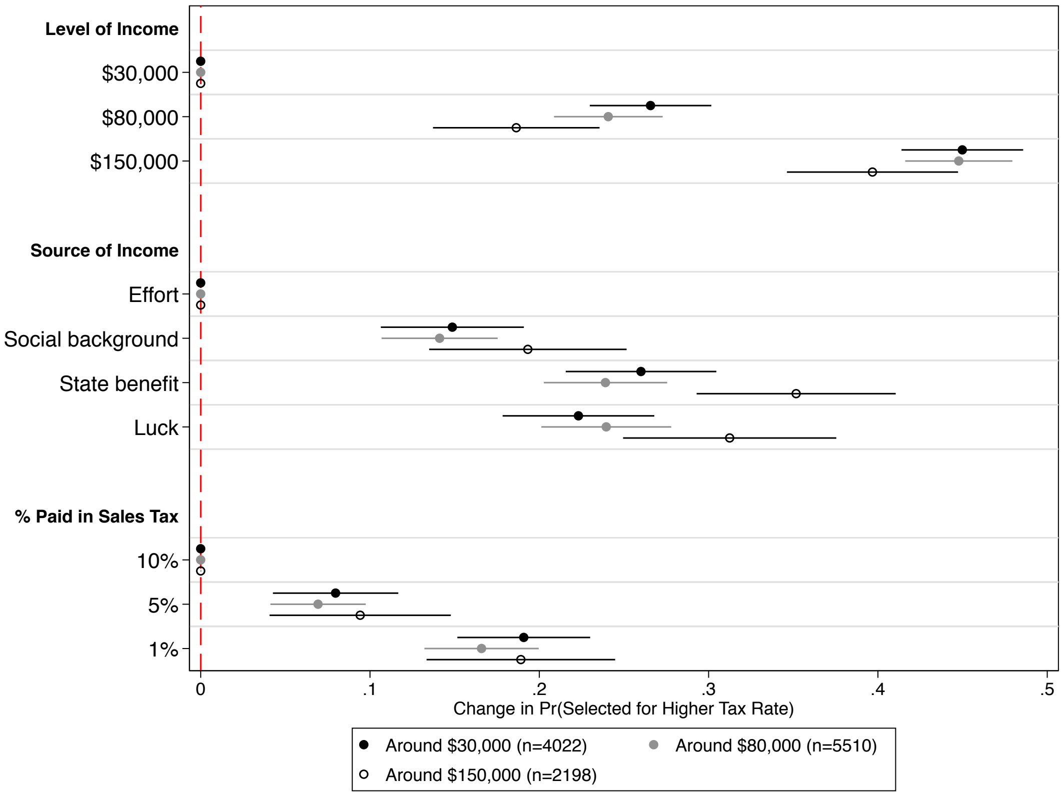
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of respondents: those with annual incomes up to $29,999 (low), between $30,000 and $79,999 (medium), and above $80,000 (high). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 24: Effect of Profile Attributes by Respondent Income Level: Low-Medium-High-Very High



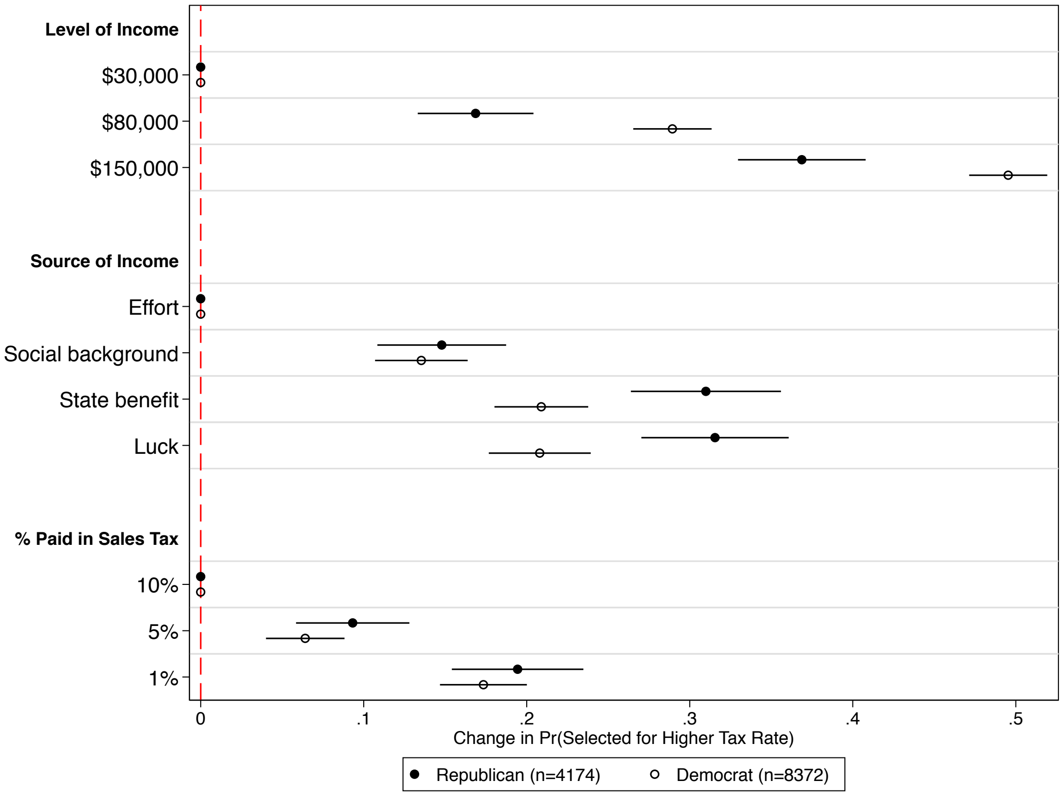
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for four different groups of respondents: those with annual incomes of $125,000 or above (very high income), between $80,000 and $124,999 (high income), between $30,000 and $79,999 (medium income), and under $30,000 (low income). The points without horizontal bars denote the attribute value that is the reference category for each attribute. This analysis not included in pre-analysis plan.

Figure 25: Effect of Profile Attributes by Margins of Respondent Income



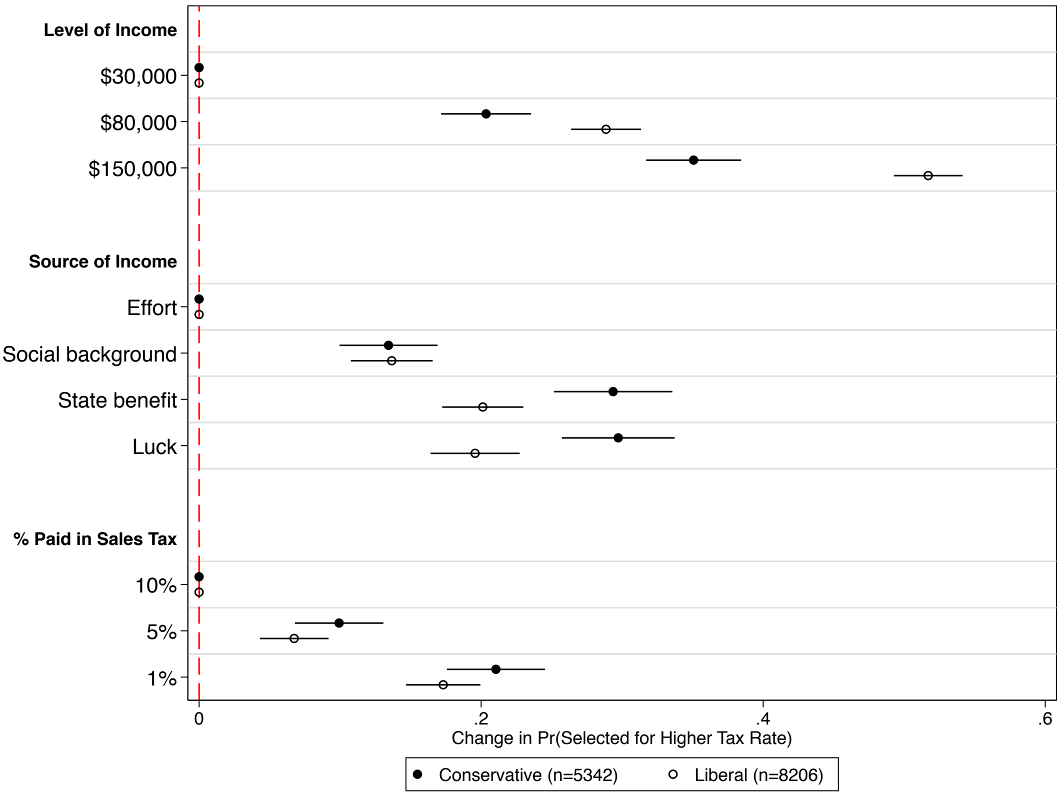
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of respondents: those with annual incomes between \$20,000 and \$39,999 (around \$30,000), between \$50,000 and \$99,999 (around \$80,000), and between \$125,000 and \$199,999 (around \$150,000). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 26: Effect of Profile Attributes by Respondent Party Identification



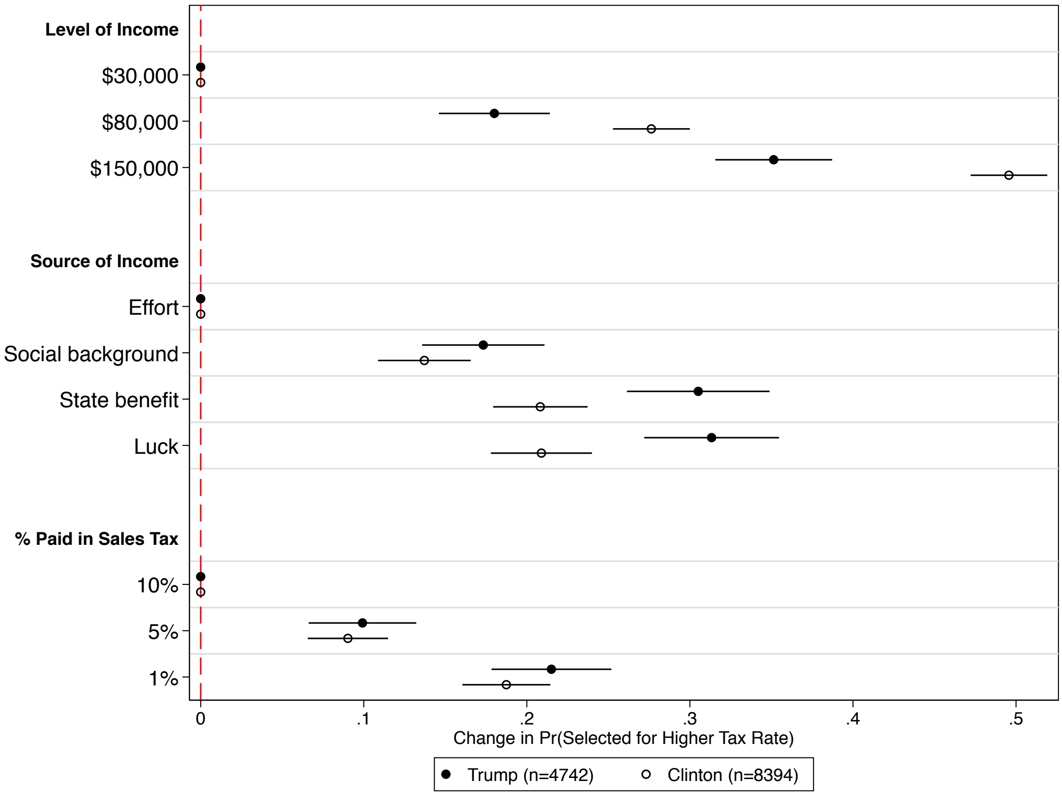
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those who identify as Republicans, and those who identify as Democrats. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 27: Effect of Profile Attributes by Respondent Ideology



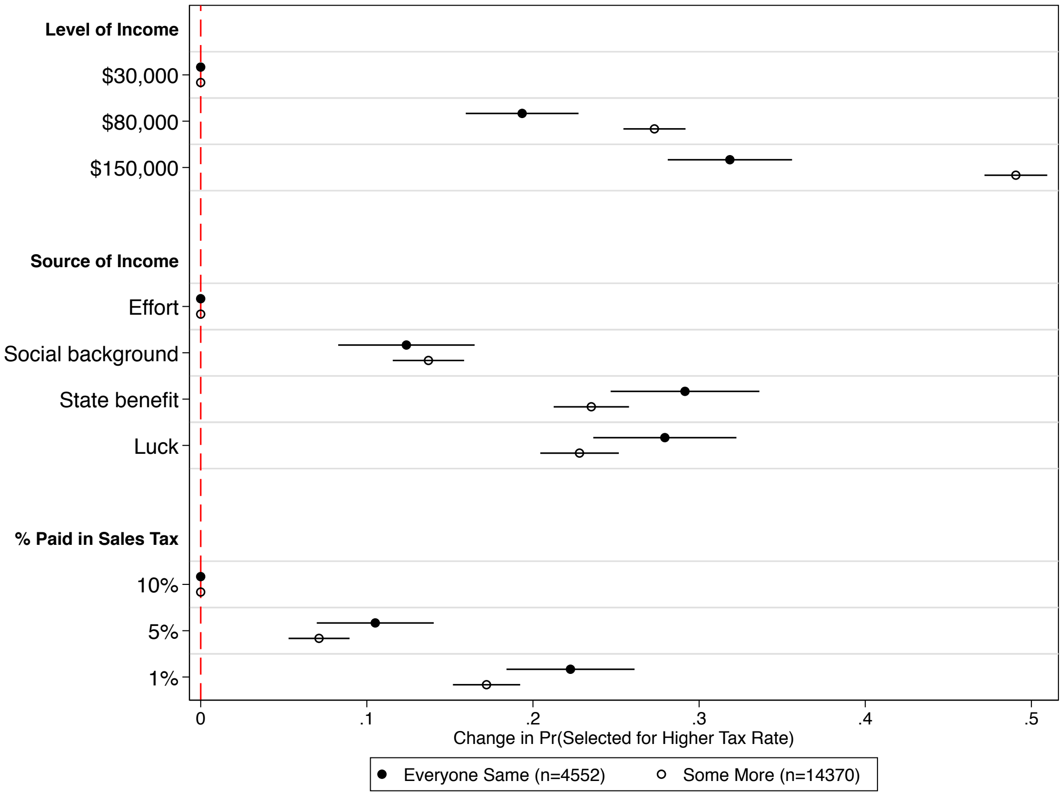
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: conservatives and liberals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 28: Effect of Profile Attributes by Respondent 2016 Vote Choice



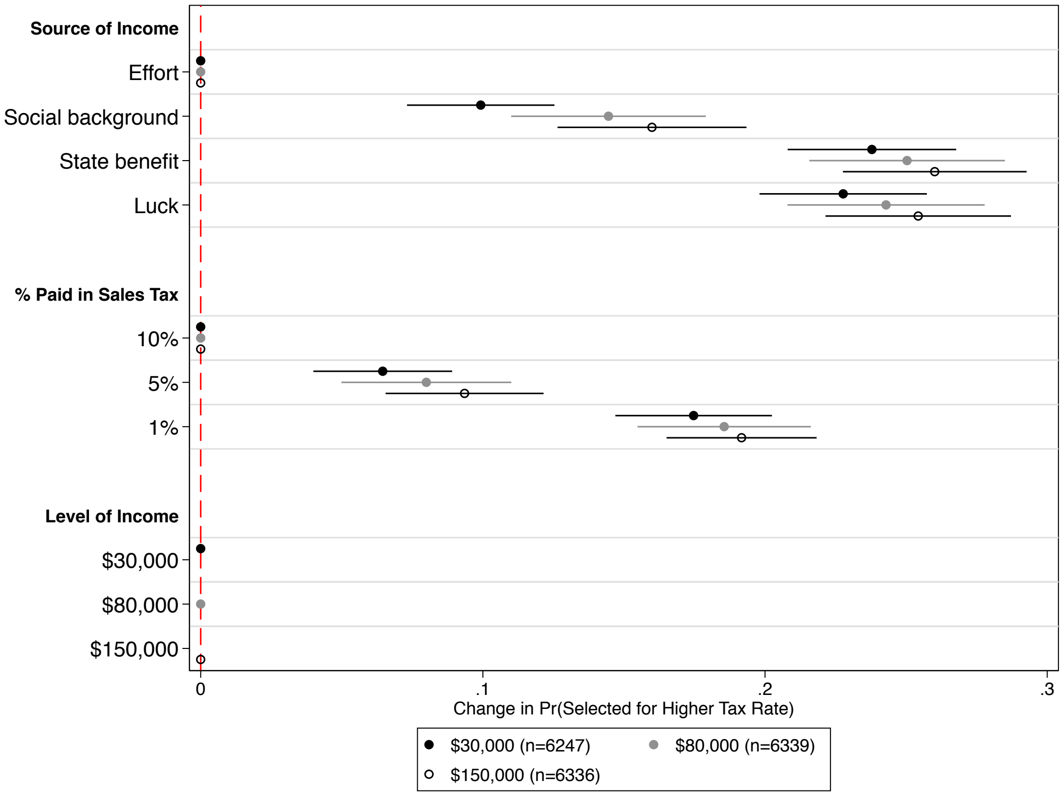
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two groups of respondents: those who voted for Trump and those who voted for Clinton in the 2016 presidential election. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 29: Effect of Profile Attributes by Respondent Adherence to Equal Treatment



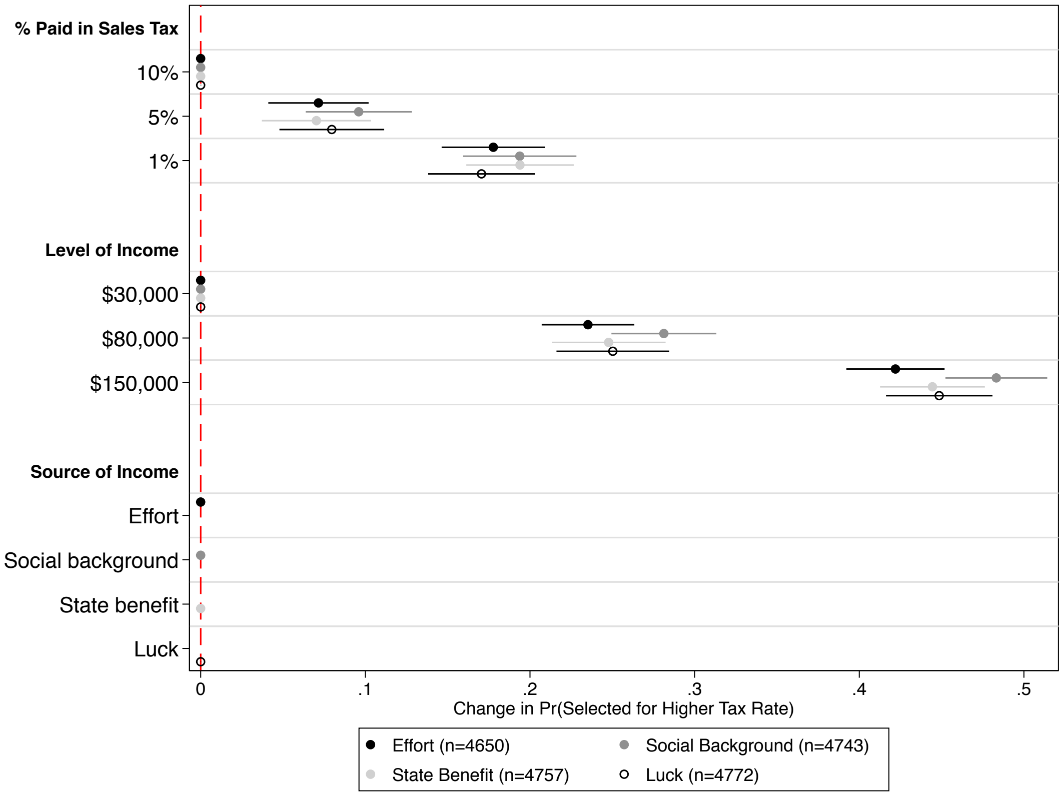
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for two different groups of respondents: those who think everyone should pay the same share of their income in taxes, and those who think some people should pay more than others. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 30: Effect of Profile Attributes by Level of Income in Profile



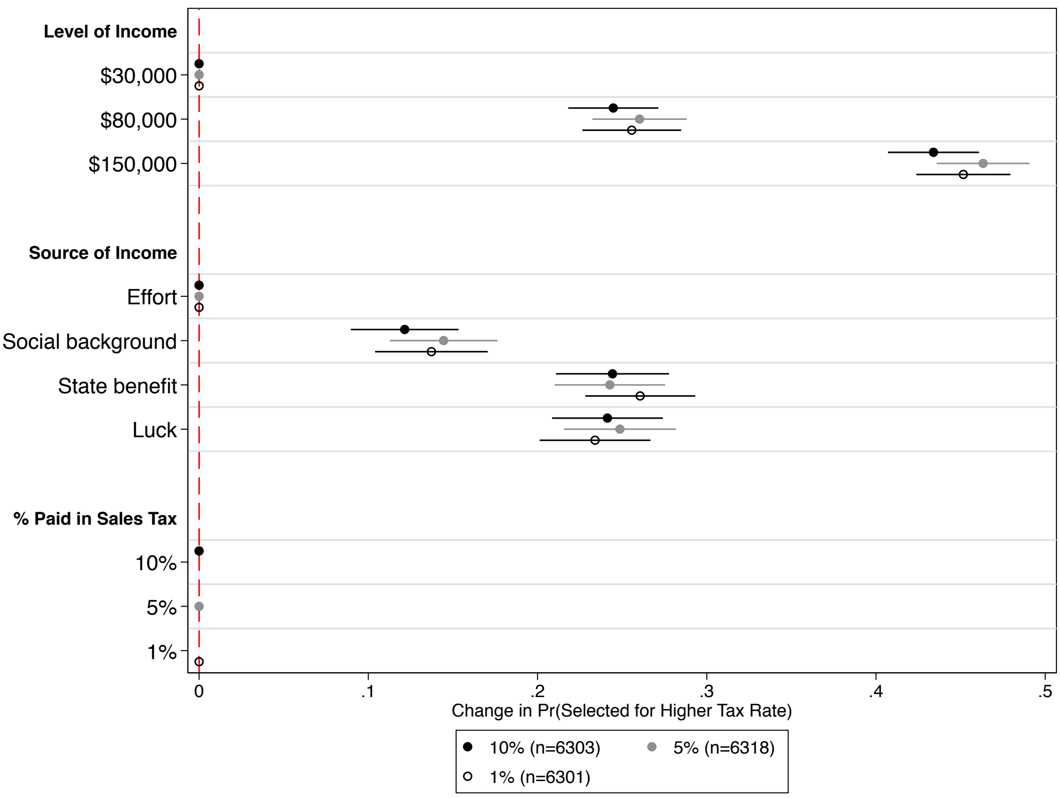
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of profiles: those with income level $30,000, those with income level $80,000 and those with income level $150,000. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 31: Effect of Profile Attributes by Source of Income in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for four different groups of profiles: those with source of income "Started own small business" (effort), those with source of income "Got a job through family connections" (social background), those with source of income "Owns business that was bailed out by the government" (state benefit), and those with source of income "Receives annuity from lottery prize" (luck). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

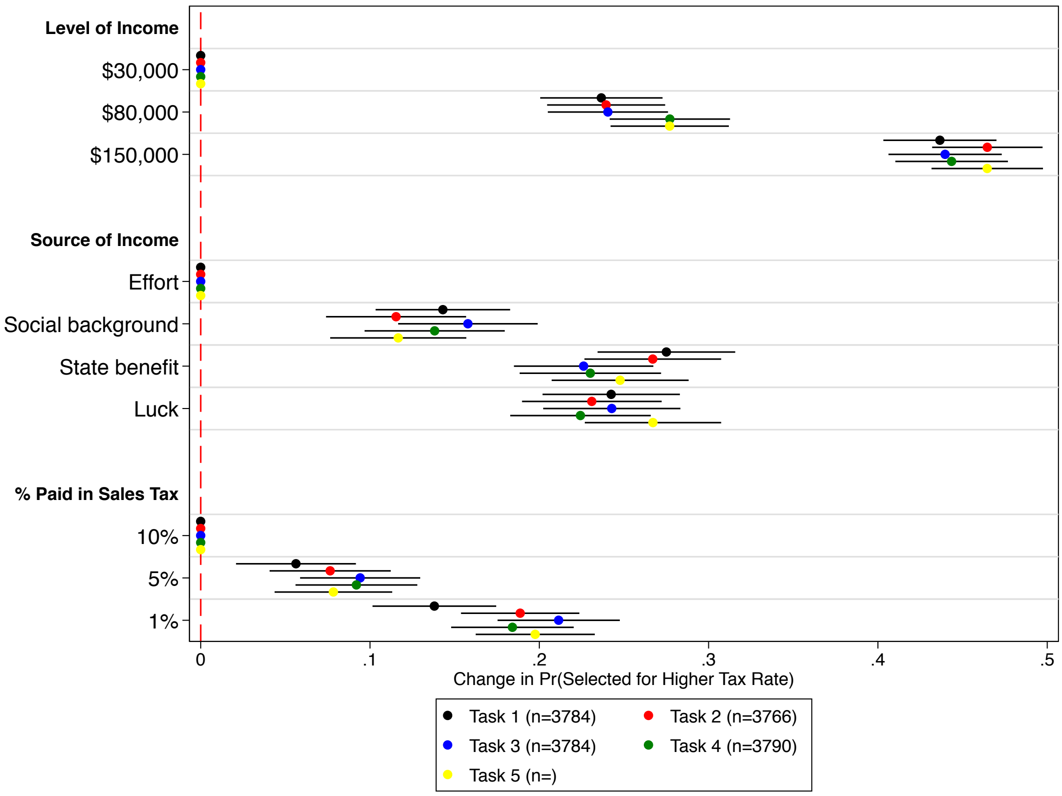
Figure 32: Effect of Profile Attributes by Share of Income Paid in Sales Tax in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for three different groups of profiles: those with percentage of income paid in sales tax of 1, 5 and 10%. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

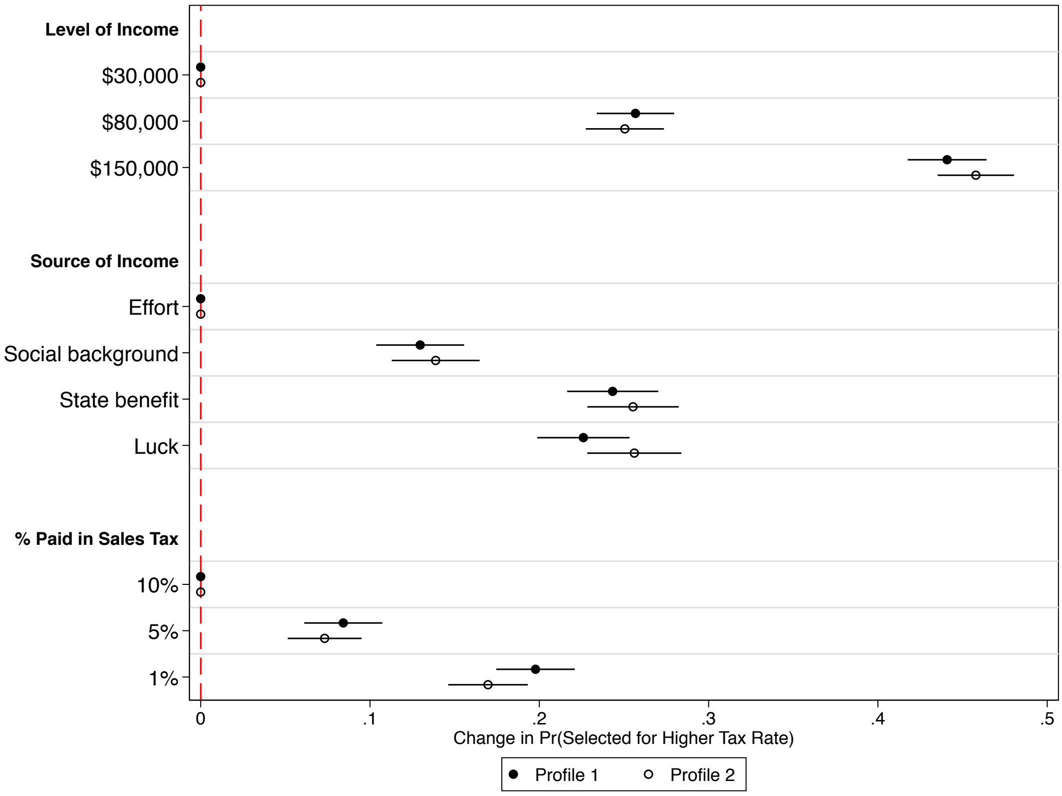
A.4 Diagnostic and Robustness Tests

Figure 33: Effect of Profile Attributes by Task



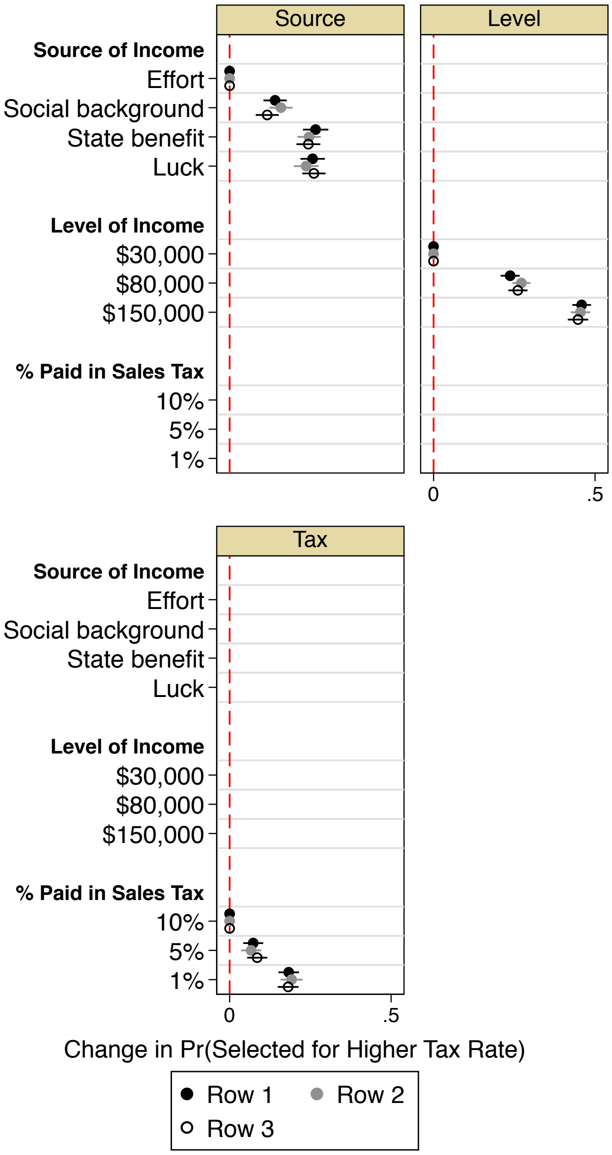
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents' first, second, third, fourth and fifth conjoint tasks. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 34: Effect of Profile Attributes by Profile Number



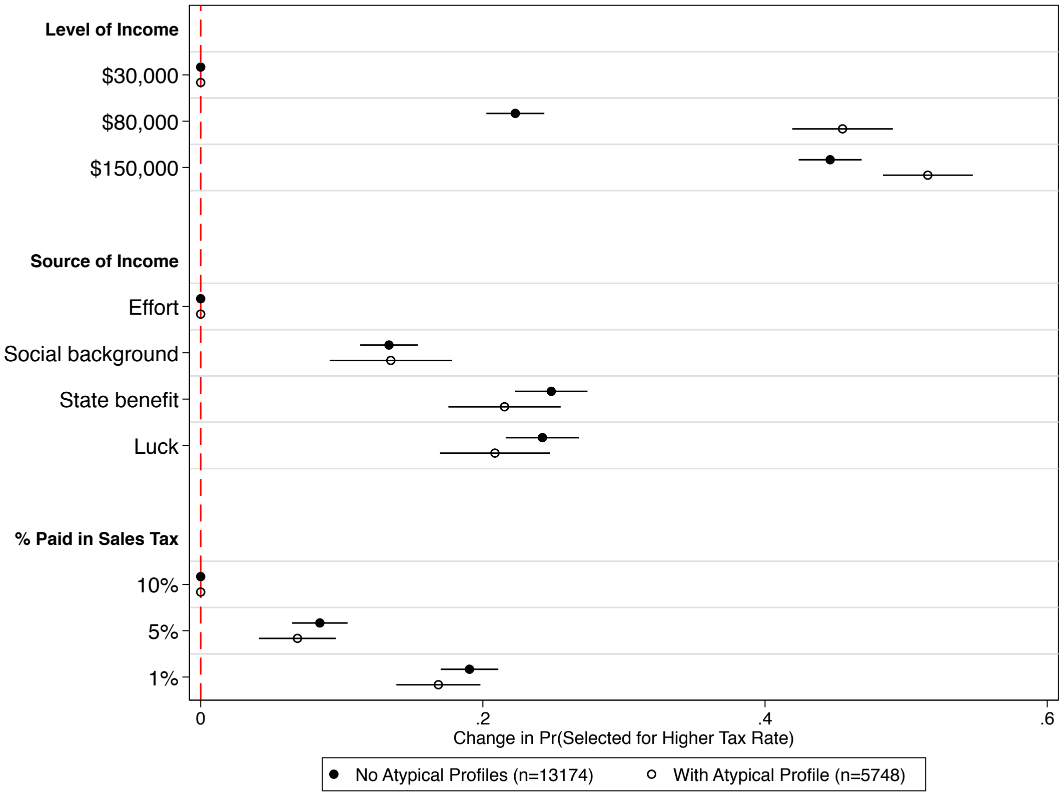
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents' first and second profile in each task. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 35: Effect of Profile Attributes by Attribute Row



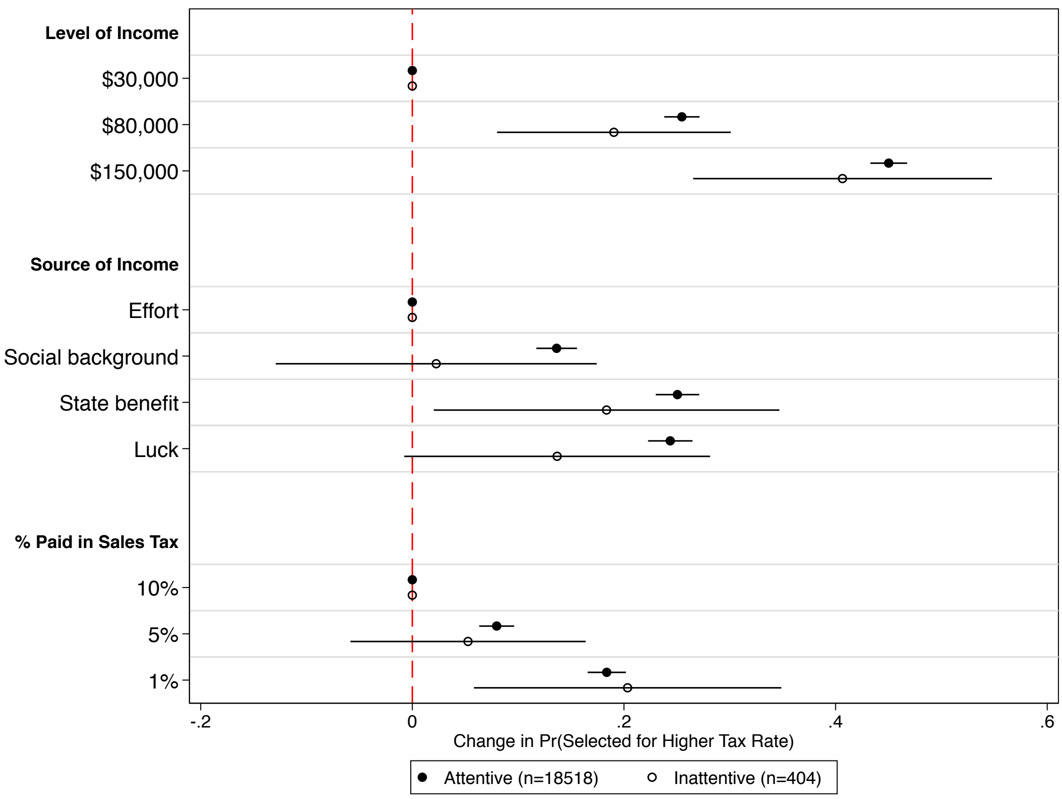
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents who saw attributes in the first, second or third row of the conjoint table. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 36: Effect of Profile Attributes by Presence of Atypical Profiles



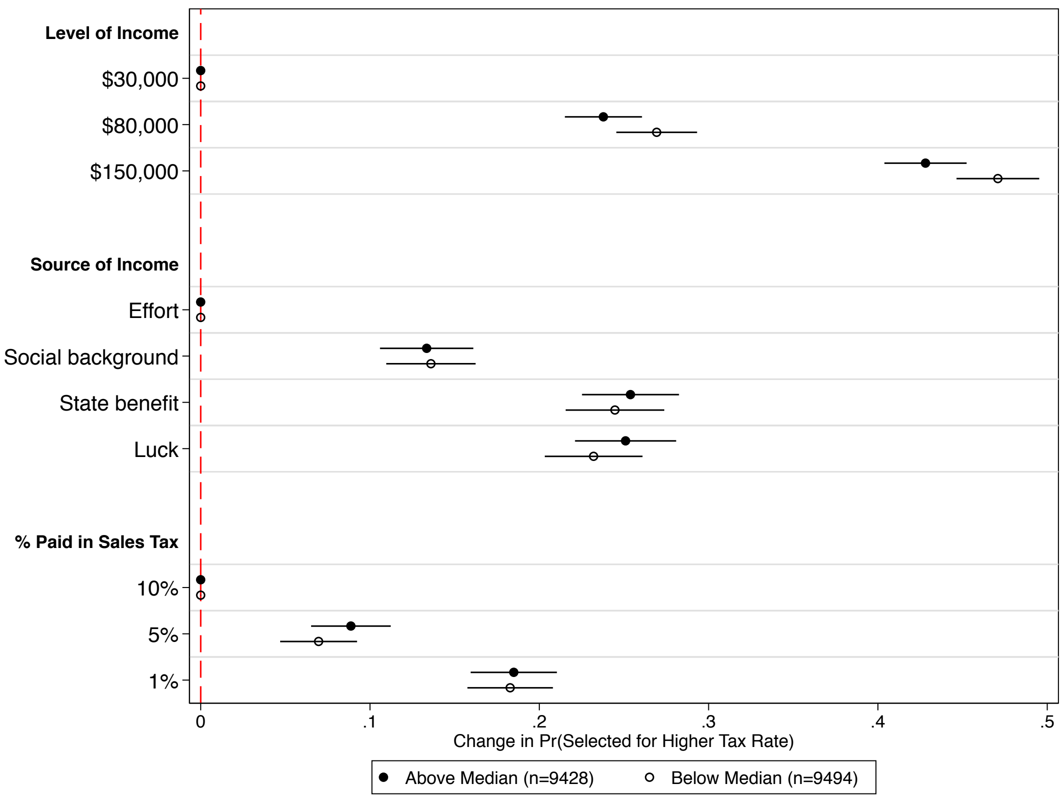
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for profiles including and not including atypical combinations (luck or state benefit and $30,000 income). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 37: Effect of Profile Attributes by Respondent Attention



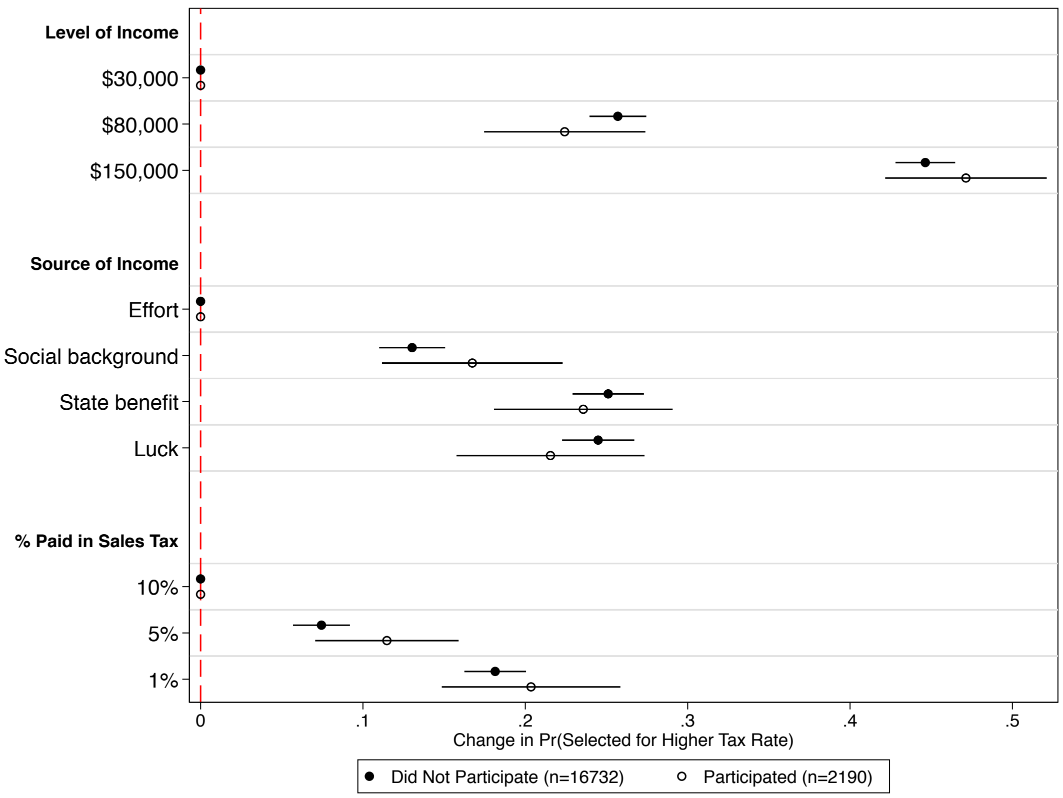
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents who passed and failed the attention screener. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 38: Effect of Profile Attributes by Respondent Speed



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents who completed the survey above and below the median time (231 seconds). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 39: Effect of Profile Attributes by Respondent Participation in Formative Study



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent, estimated for respondents who did and did not participate in the formative study. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

VARIABLES	Test 1	Test 2
Level of Income		
$80,000	0.265***	0.258***
	[0.011]	[0.016]
	[0.000]	[0.000]
$150,000	0.461***	0.474***
	[0.012]	[0.016]
	[0.000]	[0.000]
Above median	0.011	
	[0.011]	
	[0.307]	
30-39		-0.002
		[0.013]
		[0.864]
40-49		0.018
		[0.016]
		[0.251]
50-59		0.019
		[0.019]
		[0.326]
60 and over		0.030
		[0.025]
		[0.230]
$80,000#Above median	-0.018	
	[0.017]	
	[0.284]	
$150,000#Above median	-0.017	
	[0.018]	
	[0.350]	
$80,000#30-39		0.019
		[0.021]
		[0.357]
$80,000#40-49		-0.014
		[0.026]
		[0.577]
$80,000#50-59		-0.021
		[0.031]
		[0.495]
$80,000#60 and over		-0.061
		[0.039]
		[0.121]
$150,000#30-39		-0.018
		[0.021]
		[0.401]
$150,000#40-49		-0.045
		[0.028]
		[0.106]
$150,000#50-59		-0.024
		[0.033]
		[0.468]
$150,000#60 and over		-0.056
		[0.040]
		[0.167]
Reference category	Below Median	18-29
Observations	18,922	18,922
R-squared	0.138	0.138
F-test p-value	0.516	0.311

NOTES. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 4: Age - Multiple Comparisons I: Level of Income

VARIABLES	Test 1	Test 2
Source of income		
Social background	0.129***	0.132***
	[0.014]	[0.020]
	[0.000]	[0.000]
	(0.000)	(0.000)
State benefit	0.237***	0.225***
	[0.015]	[0.021]
	[0.000]	[0.000]
	(0.000)	(0.000)
Luck	0.231***	0.220***
	[0.015]	[0.020]
	[0.000]	[0.000]
	(0.000)	(0.000)
Above median	-0.026	
	[0.013]	
	[0.052]	
	(0.112)	
30-39		-0.014
		[0.016]
		[0.406]
		(0.542)
40-49		-0.058**
		[0.020]
		[0.003]
		(0.009)
50-59		-0.022
		[0.025]
		[0.380]
		(0.532)
60 and over		0.007
		[0.030]
		[0.813]
		(0.863)
Social background#Above median	0.021	
	[0.021]	
	[0.315]	
	(0.491)	
State benefit#Above median	0.032	
	[0.022]	
	[0.144]	
	(0.288)	
Luck#Above median	0.045*	
	[0.022]	
	[0.040]	
	(0.093)	
Social background#30-39		-0.006
		[0.026]
		[0.822]
		(0.863)
Social background#40-49		0.036
		[0.031]
		[0.249]
		(0.436)
Social background#50-59		0.020
		[0.038]
		[0.605]
		(0.705)
Social background#60 and over		-0.002
		[0.046]
		[0.972]
		(0.972)

(Continues in next page)

State benefit#30-39		0.032
		[0.027]
		[0.241]
		(0.436)
State benefit#40-49		0.086**
		[0.033]
		[0.010]
		(0.025)
State benefit#50-59		0.031
		[0.040]
		[0.438]
		(0.557)
State benefit#60 and over		-0.047
		[0.050]
		[0.345]
		(0.509)
Luck#30-39		0.028
		[0.027]
		[0.305]
		(0.491)
Luck#40-49		0.105***
		[0.032]
		[0.001]
		(0.003)
Luck#50-59		0.026
		[0.041]
		[0.526]
		(0.640)
Luck#60 and over		0.011
		[0.050]
		[0.832]
		(0.863)
Reference category	Below median	18-29
Observations	18,922	18,922
R-squared	0.043	0.044
F-test p-value	0.205	0.097

NOTES. Robust standard errors clustered by respondent and p-values in brackets. Q-values calculated using the Simes procedure in parentheses.
*** p<0.001, ** p<0.01, * p<0.05.

Table 5: Age - Multiple Comparisons II: Source of Income

VARIABLES	Test 1	Test 2
% paid in sales taxes		
5%	0.070***	0.072***
	[0.012]	[0.016]
	[0.000]	[0.000]
1%	0.175***	0.176***
	[0.013]	[0.018]
	[0.000]	[0.000]
Above median	-0.010	
	[0.011]	
	[0.357]	
30-39		0.004
		[0.013]
		[0.771]
40-49		-0.020
		[0.017]
		[0.245]
50-59		-0.002
		[0.020]
		[0.906]
60 and over		-0.026
		[0.023]
		[0.242]
5%#Above median	0.011	
	[0.018]	
	[0.547]	
1%#Above median	0.022	
	[0.019]	
	[0.243]	
5%#30-39		-0.008
		[0.022]
		[0.724]
5%#40-49		0.015
		[0.028]
		[0.598]
5%#50-59		-0.005
		[0.034]
		[0.873]
5%#60 and over		0.059
		[0.039]
		[0.133]
1%#30-39		-0.006
		[0.024]
		[0.798]
1%#40-49		0.045
		[0.030]
		[0.130]
1%#50-59		0.017
		[0.034]
		[0.612]
1%#60 and over		0.027
		[0.040]
		[0.501]
Reference category	Below median	18-29
Observations	18,922	18,922
R-squared	0.023	0.024
F-test p-value	0.506	0.587

NOTES. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 6: Age - Multiple Comparisons III: Percentage Paid in Sales Taxes

VARIABLES	Test 1	Test 2
Level of income		
$80,000	0.264***	0.264***
	[0.029]	[0.029]
	[0.000]	[0.000]
$150,000	0.427***	0.427***
	[0.030]	[0.030]
	[0.000]	[0.000]
High education	-0.011	
	[0.018]	
	[0.537]	
Medium education		-0.009
		[0.018]
		[0.630]
High education		-0.022
		[0.021]
		[0.293]
$80,000#High education	-0.008	
	[0.030]	
	[0.792]	
$150,000#High education	0.029	
	[0.031]	
	[0.343]	
$80,000#Medium education		-0.010
		[0.030]
		[0.736]
$80,000#High education		0.003
		[0.035]
		[0.939]
$150,000#Medium education		0.027
		[0.031]
		[0.397]
$150,000#High education		0.042
		[0.036]
		[0.240]
Reference category	Low education	Low education
Observations	18,922	18,922
R-squared	0.138	0.138
F-test p-value	0.397	0.664

NOTES. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 7: Level of Education - Multiple Comparisons I: Level of Income

VARIABLES	Test 1	Test 2
Source of income		
Social background	0.104**	0.104**
	[0.034]	[0.034]
	[0.002]	[0.002]
State benefit	0.204***	0.204***
	[0.036]	[0.036]
	[0.000]	[0.000]
Luck	0.232***	0.232***
	[0.034]	[0.034]
	[0.000]	[0.000]
High education	-0.027	
	[0.022]	
	[0.227]	
Medium education		-0.029
		[0.022]
		[0.197]
High education		-0.017
		[0.027]
		[0.529]
Social background#High education	0.038	
	[0.036]	
	[0.294]	
State benefit#High education	0.052	
	[0.038]	
	[0.170]	
Luck#High education	0.022	
	[0.036]	
	[0.550]	
Social background#Medium education		0.042
		[0.036]
		[0.243]
Social background#High education		0.017
		[0.044]
		[0.704]
State benefit#Medium education		0.059
		[0.039]
		[0.125]
State benefit#High education		0.021
		[0.045]
		[0.638]
Luck#Medium education		0.019
		[0.037]
		[0.609]
Luck#High education		0.035
		[0.044]
		[0.426]
Reference category	Low education	Low education
Observations	18,922	18,922
R-squared	0.043	0.043
F-test p-value	0.544	0.416

Notes. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 8: Level of Education - Multiple Comparisons II: Source of Income

VARIABLES	Test 1	Test 2
% paid in sales taxes		
5%	0.078**	0.078**
	[0.030]	[0.030]
	[0.008]	[0.008]
1%	0.214***	0.214***
	[0.031]	[0.031]
	[0.000]	[0.000]
High education	0.012	
	[0.019]	
	[0.510]	
Medium education		0.013
		[0.019]
		[0.503]
High education		0.011
		[0.023]
		[0.632]
5%#High education	-0.004	
	[0.031]	
	[0.906]	
1%#High education	-0.032	
	[0.033]	
	[0.328]	
5%#Medium education		-0.004
		[0.031]
		[0.905]
5%#High education		-0.003
		[0.038]
		[0.929]
1%#Medium education		-0.032
		[0.033]
		[0.324]
1%#High education		-0.029
		[0.039]
		[0.464]
Reference category	Low education	Low education
Observations	18,922	18,922
R-squared	0.023	0.023
F-test p-value	0.556	0.879

NOTES. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 9: Level of Education - Multiple Comparisons III: Percentage Paid in Sales Taxes

VARIABLES	Test 1	Test 2
Level of Income		
$80,000	0.256***	0.254***
	[0.010]	[0.011]
	[0.000]	[0.000]
$150,000	0.455***	0.453***
	[0.010]	[0.012]
	[0.000]	[0.000]
Unemployed	-0.021	-0.021
	[0.023]	[0.023]
	[0.351]	[0.362]
Not in labor force (incl. students)	0.009	
	[0.015]	
	[0.551]	
Part-time Employee		0.011
		[0.017]
		[0.544]
Self Employed		-0.007
		[0.017]
		[0.679]
Student		0.008
		[0.027]
		[0.751]
Not in Labor Force		0.009
		[0.017]
		[0.594]
$80,000# Unemployed	0.046	0.049
	[0.035]	[0.036]
	[0.186]	[0.170]
$80,000#Not in labor force (incl. students)	-0.014	
	[0.024]	
	[0.570]	
$150,000# Unemployed	0.022	0.024
	[0.042]	[0.042]
	[0.597]	[0.569]
$150,000#Not in labor force (incl. students)	-0.016	
	[0.024]	
	[0.502]	
$80,000#Part-time Employee		0.011
		[0.029]
		[0.718]
$80,000#Self Employed		0.009
		[0.028]
		[0.744]
$80,000#Student		-0.001
		[0.043]
		[0.980]
$80,000#Not in Labor Force		-0.016
		[0.029]
		[0.579]
$150,000#Part-time Employee		-0.010
		[0.032]
		[0.762]
$150,000#Self Employed		0.021
		[0.029]
		[0.481]
$150,000#Student		-0.033
		[0.045]
		[0.472]
$150,000#Not in Labor Force		-0.007
		[0.028]
		[0.794]
Reference category	Employed	Full-time Employee
Observations	18,922	18,922
R-squared	0.138	0.138
F-test p-value	0.648	0.941

NOTES. Robust standard errors clustered by respondent and p-values in brackets. *** p<0.001, ** p<0.01, * p<0.05.

Table 10: Employment Status - Multiple Comparisons I: Level of Income

VARIABLES	Test 1	Test 2
Source of Income		
Social background	0.131***	0.136***
	[0.012]	[0.014]
	[0.000]	[0.000]
State benefit	0.245***	0.246***
	[0.012]	[0.015]
	[0.000]	[0.000]
Luck	0.252***	0.255***
	[0.012]	[0.015]
	[0.000]	[0.000]
Unemployed	0.017	0.020
	[0.025]	[0.026]
	[0.504]	[0.446]
Not in labor force (incl. students)	-0.034	
	[0.018]	
	[0.067]	
Part-time Employee		0.023
		[0.023]
		[0.317]
Self Employed		0.001
		[0.020]
		[0.946]
Student		-0.068*
		[0.032]
		[0.035]
Not in Labor Force		-0.017
		[0.022]
		[0.443]
Social background# Unemployed	0.006	0.001
	[0.046]	[0.046]
	[0.892]	[0.988]
Social background#Not in labor force (incl. students)	0.051	
	[0.028]	
	[0.075]	
State benefit# Unemployed	0.008	0.007
	[0.042]	[0.042]
	[0.840]	[0.860]
State benefit#Not in labor force (incl. students)	0.043	
	[0.031]	
	[0.165]	
Luck# Unemployed	-0.075	-0.078
	[0.048]	[0.048]
	[0.114]	[0.104]
Luck#Not in labor force (incl. students)	0.031	
	[0.031]	
	[0.318]	
Social background#Part-time Employee		-0.037
		[0.037]
		[0.318]
Social background#Self Employed		-0.009
		[0.034]
		[0.787]
Social background#Student		0.087
		[0.047]
		[0.065]
Social background#Not in Labor Force		0.029
		[0.034]
		[0.394]
State benefit#Part-time Employee		0.001
		[0.040]
		[0.978]
State benefit#Self Employed		-0.008
		[0.034]
		[0.809]
State benefit#Student		0.111*
		[0.055]
		[0.044]
State benefit#Not in Labor Force		0.014
		[0.037]
		[0.703]
Luck#Part-time Employee		-0.058
		[0.039]
		[0.134]
Luck#Self Employed		0.025
		[0.034]
		[0.470]
Luck#Student		0.046
		[0.053]
		[0.390]
Luck#Not in Labor Force		0.021
		[0.036]
		[0.569]
Reference category	Employed	Full-time Employee
Observations	18,922	18,922
R-squared	0.043	0.044
F-test p-value	0.294	0.455

Notes. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 11: Employment Status - Multiple Comparisons II: Source of Income

VARIABLES	Test 1	Test 2
% paid in sales taxes		
5%	0.075***	0.080***
	[0.010]	[0.012]
	[0.000]	[0.000]
1%	0.180***	0.186***
	[0.011]	[0.013]
	[0.000]	[0.000]
Unemployed	-0.021	-0.017
	[0.023]	[0.023]
	[0.353]	[0.456]
Not in labor force (incl. students)	-0.005	
	[0.015]	
	[0.722]	
Part-time Employee		0.003
		[0.019]
		[0.885]
Self Employed		0.024
		[0.017]
		[0.159]
Student		-0.000
		[0.027]
		[0.986]
Not in Labor Force		-0.002
		[0.017]
		[0.928]
5%#Unemployed	0.046	0.041
	[0.037]	[0.038]
	[0.215]	[0.277]
5%#Not in labor force (incl. students)	-0.015	
	[0.025]	
	[0.536]	
1%#Unemployed	0.018	0.012
	[0.043]	[0.043]
	[0.683]	[0.785]
1%#Not in labor force (incl. students)	0.028	
	[0.026]	
	[0.278]	
5%#Part-time Employee		-0.014
		[0.031]
		[0.642]
5%#Self Employed		-0.022
		[0.029]
		[0.448]
5%#Student		-0.024
		[0.043]
		[0.571]
5%#Not in Labor Force		-0.019
		[0.029]
		[0.524]
1%#Part-time Employee		0.009
		[0.034]
		[0.792]
1%#Self Employed		-0.045
		[0.031]
		[0.148]
1%#Student		0.013
		[0.047]
		[0.776]
1%#Not in Labor Force		0.027
		[0.031]
		[0.385]
Reference category	Employed	Full-time Employee
Observations	18,922	18,922
R-squared	0.023	0.024
F-test p-value	0.285	0.642

NOTES. Robust standard errors clustered by respondent and p-values in brackets. *** p<0.001, ** p<0.01, * p<0.05.

Table 12: Employment Status - Multiple Comparisons III: Percentage Paid in Sales Taxes

VARIABLES	Test 1: Zip code level Inequality	Test 2: State level Inequality
Level of income		
$80,000	0.230***	0.268***
	[0.016]	[0.015]
	[0.000]	[0.000]
	(0.000)	(0.000)
$150,000	0.420***	0.454***
	[0.016]	[0.016]
	[0.000]	[0.000]
	(0.000)	(0.000)
Medium inequality	-0.028*	0.007
	[0.013]	[0.012]
	[0.025]	[0.587]
	(0.050)	(0.754)
High inequality	-0.033*	-0.004
	[0.014]	[0.014]
	[0.015]	[0.769]
	(0.033)	(0.783)
$80,000#Medium inequality	0.045*	-0.025
	[0.021]	[0.020]
	[0.028]	[0.222]
	(0.050)	(0.307)
$80,000#High inequality	0.031	-0.006
	[0.022]	[0.022]
	[0.169]	[0.776]
	(0.253)	(0.783)
$150,000#Medium inequality	0.043*	-0.007
	[0.022]	[0.021]
	[0.046]	[0.757]
	(0.075)	(0.783)
$150,000#High inequality	0.062**	0.006
	[0.023]	[0.023]
	[0.007]	[0.783]
	(0.018)	(0.783)
Reference category	Low inequality	Low inequality
Observations	18,592	18,852
R-squared	0.139	0.137
F-test p-value	0.037	0.744

NOTES. Robust standard errors clustered by respondent and p-values in brackets. Q-values calculated using the Simes procedure in parentheses.
*** p<0.001, ** p<0.01, * p<0.05.

Table 13: Inequality in Place of Residence - Multiple Comparisons I: Level of Income

VARIABLES	Test 1: Zip code level Inequality	Test 2: State level Inequality
Source of income		
Social background	0.151***	0.127***
	[0.019]	[0.019]
	[0.000]	[0.000]
	(0.000)	(0.000)
State benefit	0.280***	0.233***
	[0.020]	[0.020]
	[0.000]	[0.000]
	(0.000)	(0.000)
Luck	0.281***	0.237***
	[0.020]	[0.020]
	[0.000]	[0.000]
	(0.000)	(0.000)
Medium inequality	0.028	-0.029
	[0.016]	[0.015]
	[0.087]	[0.061]
	(0.174)	(0.147)
High inequality	0.019	0.003
	[0.017]	[0.018]
	[0.259]	[0.856]
	(0.365)	(0.893)
Social background#Medium inequality	-0.025	0.022
	[0.026]	[0.025]
	[0.319]	[0.383]
	(0.425)	(0.483)
Social background#High inequality	-0.000	0.007
	[0.027]	[0.028]
	[0.988]	[0.806]
	(0.988)	(0.893)
State benefit#Medium inequality	-0.040	0.059*
	[0.027]	[0.026]
	[0.131]	[0.023]
	(0.242)	(0.060)
State benefit#High inequality	-0.034	-0.016
	[0.028]	[0.029]
	[0.236]	[0.590]
	(0.354)	(0.709)
Luck#Medium inequality	-0.035	0.045
	[0.027]	[0.026]
	[0.191]	[0.086]
	(0.306)	(0.174)
Luck#High inequality	-0.038	-0.006
	[0.029]	[0.029]
	[0.189]	[0.837]
	(0.306)	(0.893)
Reference category	Low inequality	Low inequality
Observations	18,592	18,852
R-squared	0.044	0.044
F-test p-value	0.598	0.080

NOTES. Robust standard errors clustered by respondent and p-values in brackets. Q-values calculated using the Simes procedure in parentheses.
*** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table 14: Inequality in Place of Residence - Multiple Comparisons II: Source of Income

VARIABLES	Test 1: Zip code level Inequality	Test 2: State level Inequality
% paid in sales taxes		
5%	0.088***	0.080***
	[0.017]	[0.016]
	[0.000]	[0.000]
1%	0.192***	0.192***
	[0.018]	[0.018]
	[0.000]	[0.000]
Medium inequality	0.002	0.008
	[0.013]	[0.013]
	[0.893]	[0.534]
High inequality	0.024	0.003
	[0.014]	[0.014]
	[0.087]	[0.827]
5%#Medium inequality	-0.011	-0.001
	[0.022]	[0.022]
	[0.624]	[0.949]
5%#High inequality	-0.030	-0.015
	[0.024]	[0.024]
	[0.208]	[0.526]
1%#Medium inequality	0.009	-0.022
	[0.023]	[0.023]
	[0.699]	[0.339]
1%#High inequality	-0.037	0.009
	[0.025]	[0.025]
	[0.137]	[0.718]
Reference category	Low inequality	Low inequality
Observations	18,592	18,852
R-squared	0.023	0.023
F-test p-value	0.306	0.376

NOTES. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 15: Inequality in Place of Residence - Multiple Comparisons III: Percentage Paid in Sales Taxes

VARIABLES	Test 1	Test 2	Test 3
Level of Income			
$80,000	0.244***	0.273***	0.273***
	[0.012]	[0.016]	[0.016]
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.000)	(0.000)
$150,000	0.436***	0.485***	0.485***
	[0.012]	[0.017]	[0.017]
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.000)	(0.000)
High income	-0.021*	0.028*	0.012
	[0.010]	[0.013]	[0.015]
	[0.041]	[0.035]	[0.419]
	(0.069)	(0.063)	(0.435)
Medium income		0.016	0.016
		[0.013]	[0.013]
		[0.204]	[0.204]
		(0.256)	(0.256)
Very high income			0.051**
			[0.018]
			[0.004]
			(0.010)
$80,000#High income	0.029	-0.027	-0.001
	[0.017]	[0.022]	[0.024]
	[0.092]	[0.220]	[0.964]
	(0.146)	(0.259)	(0.964)
$150,000#High income	0.037*	-0.059*	-0.037
	[0.018]	[0.023]	[0.026]
	[0.035]	[0.011]	[0.163]
	(0.063)	(0.024)	(0.244)
$80,000#Medium income		-0.018	-0.018
		[0.021]	[0.021]
		[0.405]	[0.405]
		(0.435)	(0.435)
$150,000#Medium income		-0.027	-0.027
		[0.022]	[0.022]
		[0.208]	[0.208]
		(0.256)	(0.256)
$80,000#Very high income			-0.062*
			[0.029]
			[0.032]
			(0.063)
$150,000#Very high income			-0.092**
			[0.031]
			[0.003]
			(0.007)
Reference category	Low income	Low income	Low income
Observations	18,922	18,922	18,922
R-squared	0.138	0.138	0.138
F-test p-value	0.087	0.150	0.089

NOTES. Robust standard errors clustered by respondent and p-values in brackets. Q-values calculated using the Simes procedure in parentheses.
*** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table 16: Income Level - Multiple Comparisons I: Level of Income

VARIABLES	Test 1	Test 2	Test 3
Source of Income			
Social background	0.149***	0.126***	0.126***
	[0.014]	[0.020]	[0.020]
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.000)	(0.000)
State benefit	0.274***	0.218***	0.218***
	[0.015]	[0.020]	[0.020]
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.000)	(0.000)
Luck	0.283***	0.213***	0.213***
	[0.015]	[0.021]	[0.021]
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.000)	(0.000)
High income	0.036**	-0.046**	-0.034
	[0.013]	[0.017]	[0.020]
	[0.007]	[0.007]	[0.085]
	(0.013)	(0.013)	(0.133)
Medium income		-0.013	-0.013
		[0.016]	[0.016]
		[0.430]	[0.430]
		(0.469)	(0.469)
Very high income			-0.061**
			[0.021]
			[0.005]
			(0.010)
Social background #High income	-0.025	0.022	0.004
	[0.021]	[0.027]	[0.031]
	[0.243]	[0.424]	[0.904]
	(0.336)	(0.469)	(0.904)
State benefit#High income	-0.049*	0.073*	0.045
	[0.022]	[0.029]	[0.033]
	[0.026]	[0.010]	[0.176]
	(0.042)	(0.019)	(0.264)
Luck#High income	-0.068**	0.088**	0.078*
	[0.022]	[0.028]	[0.032]
	[0.002]	[0.002]	[0.016]
	(0.005)	(0.005)	(0.027)
Social background#Medium income		0.012	0.012
		[0.026]	[0.026]
		[0.657]	[0.657]
		(0.675)	(0.675)
State benefit#Medium income		0.023	0.023
		[0.027]	[0.027]
		[0.391]	[0.391]
		(0.469)	(0.469)
Luck#Medium income		0.023	0.023
		[0.027]	[0.027]
		[0.411]	[0.411]
		(0.469)	(0.469)
Social background #Very high income			0.045
			[0.035]
			[0.190]
			(0.273)
State benefit#Very high income			0.111**
			[0.036]
			[0.002]
			(0.006)
Luck#Very high income			0.101**
			[0.037]
			[0.006]
			(0.012)
Reference category	Low income	Low income	Low income
Observations	18,922	18,922	18,922
R-squared	0.043	0.044	0.044
F-test p-value	0.013	0.024	0.039

NOTES. Robust standard errors clustered by respondent and p-values in brackets. Q-values calculated using the Simes procedure in parentheses.
*** p<0.001, ** p<0.01, * p<0.05.

Table 17: Income Level - Multiple Comparisons II: Source of Income

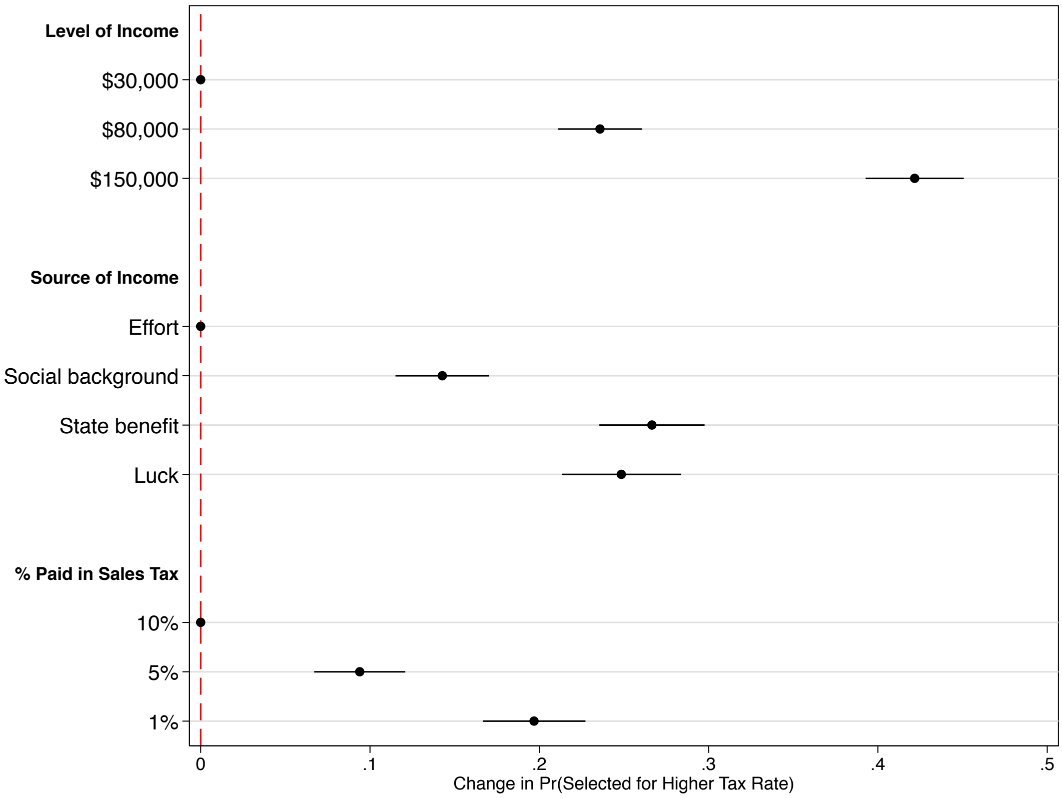
VARIABLES	Test 1	Test 2	Test 3
% paid in sales taxes			
5%	0.073***	0.061***	0.061***
	[0.012]	[0.018]	[0.018]
	[0.000]	[0.001]	[0.001]
1%	0.178***	0.162***	0.162***
	[0.013]	[0.018]	[0.018]
	[0.000]	[0.000]	[0.000]
High income	-0.006	-0.010	-0.006
	[0.011]	[0.014]	[0.016]
	[0.590]	[0.485]	[0.732]
Medium income		-0.025	-0.025
		[0.013]	[0.013]
		[0.065]	[0.065]
Very high income			-0.016
			[0.018]
			[0.392]
5%#High income	0.004	0.016	0.005
	[0.018]	[0.024]	[0.027]
	[0.838]	[0.510]	[0.846]
1%#High income	0.016	0.011	0.007
	[0.019]	[0.025]	[0.029]
	[0.418]	[0.643]	[0.795]
5%#Medium income		0.023	0.023
		[0.023]	[0.023]
		[0.315]	[0.315]
1%#Medium income		0.048*	0.048*
		[0.024]	[0.024]
		[0.043]	[0.043]
5%#Very high income			0.030
			[0.031]
			[0.334]
1%#Very high income			0.017
			[0.032]
			[0.597]
Reference category	Low income	Low income	Low income
Observations	18,922	18,922	18,922
R-squared	0.023	0.023	0.023
F-test p-value	0.698	0.280	0.462

NOTES. Robust standard errors clustered by respondent and p-values in brackets.
*** p<0.001, ** p<0.01, * p<0.05.

Table 18: Income Level - Multiple Comparisons III: Percentage Paid in Sales Taxes

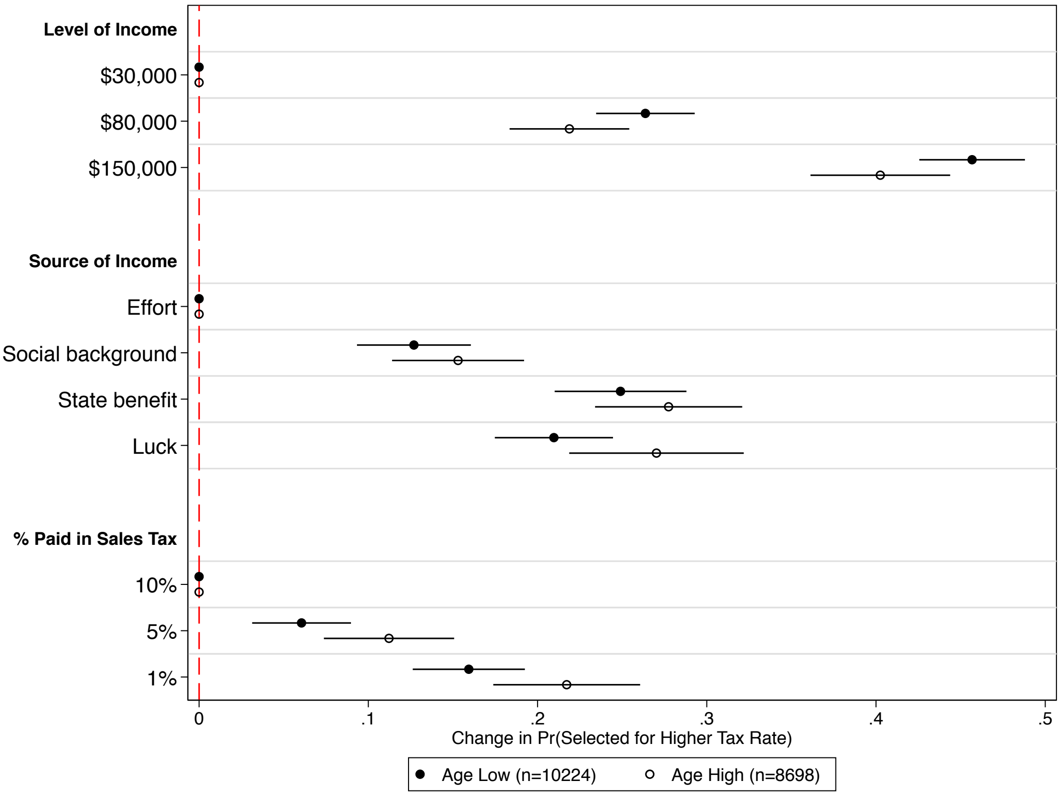
A.5 Weighted Results

Figure 40: Effect of Profile Attributes on Probability of Being Selected for Higher Tax Rate



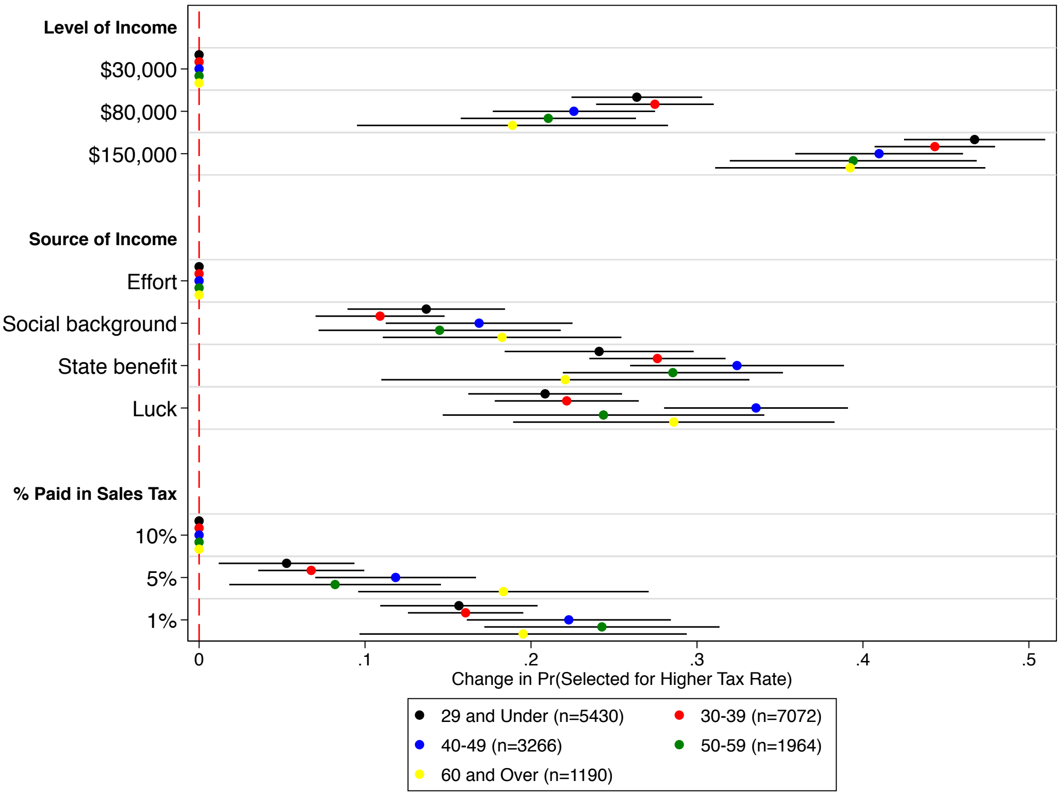
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights. Bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 41: Effect of Profile Attributes by Respondent Age



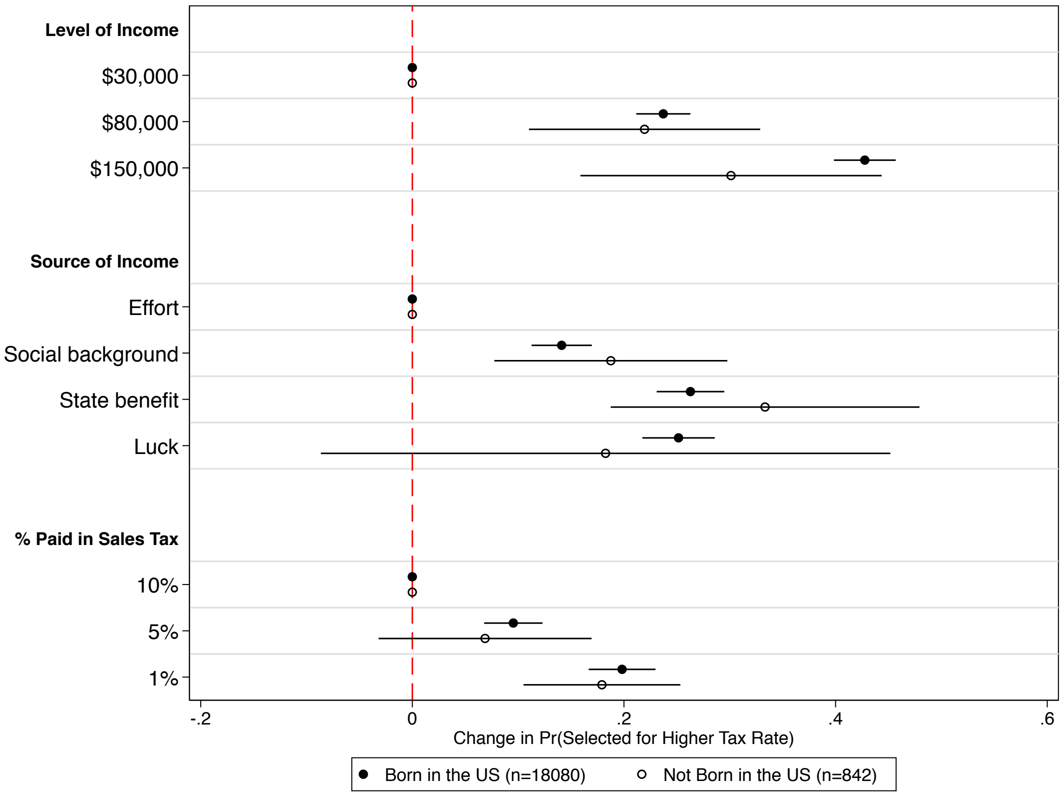
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: those with age above and below the median (35). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 42: Effect of Profile Attributes by Respondent Age Groups



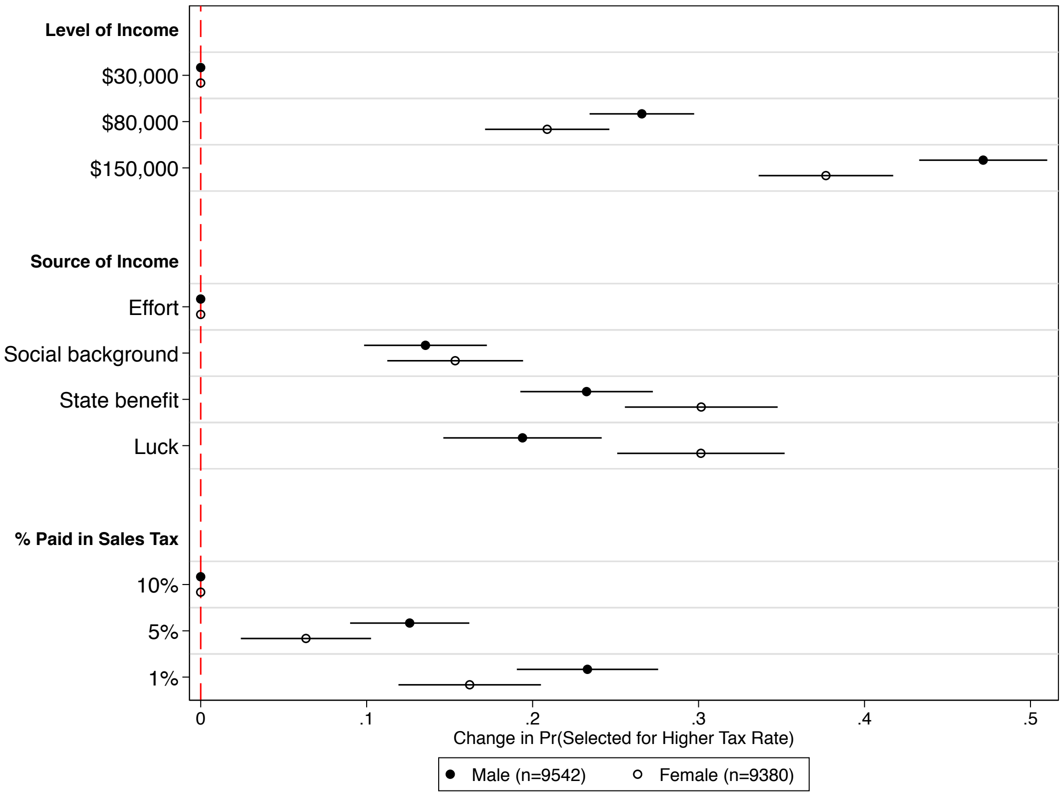
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for respondents grouped by their age. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 43: Effect of Profile Attributes by Respondent Place of Birth



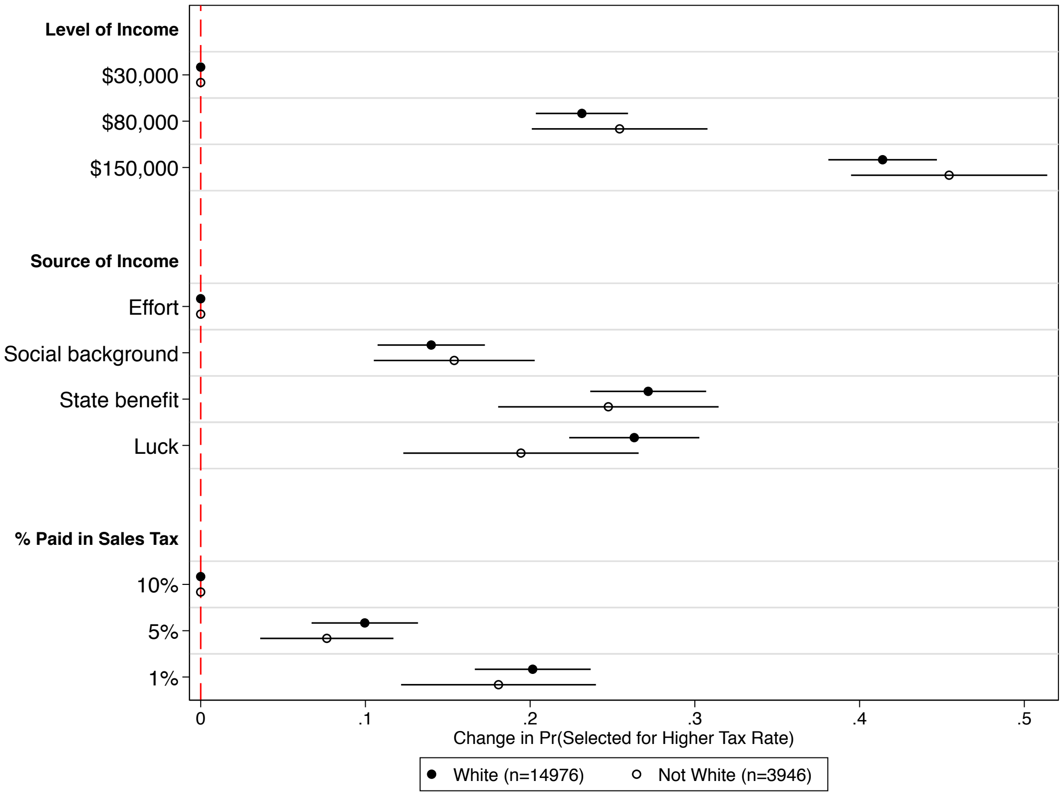
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for respondents grouped by their place of birth. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 44: Effect of Profile Attributes by Respondent Gender



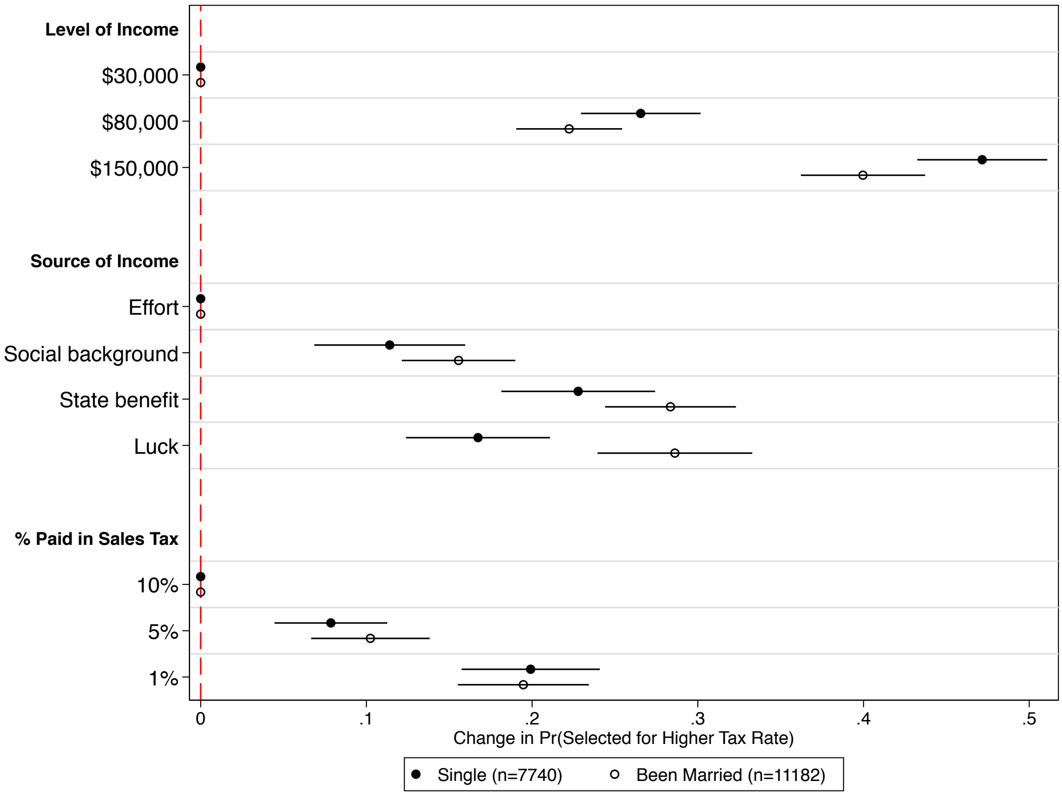
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for male and female respondents. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 45: Effect of Profile Attributes by Respondent Race



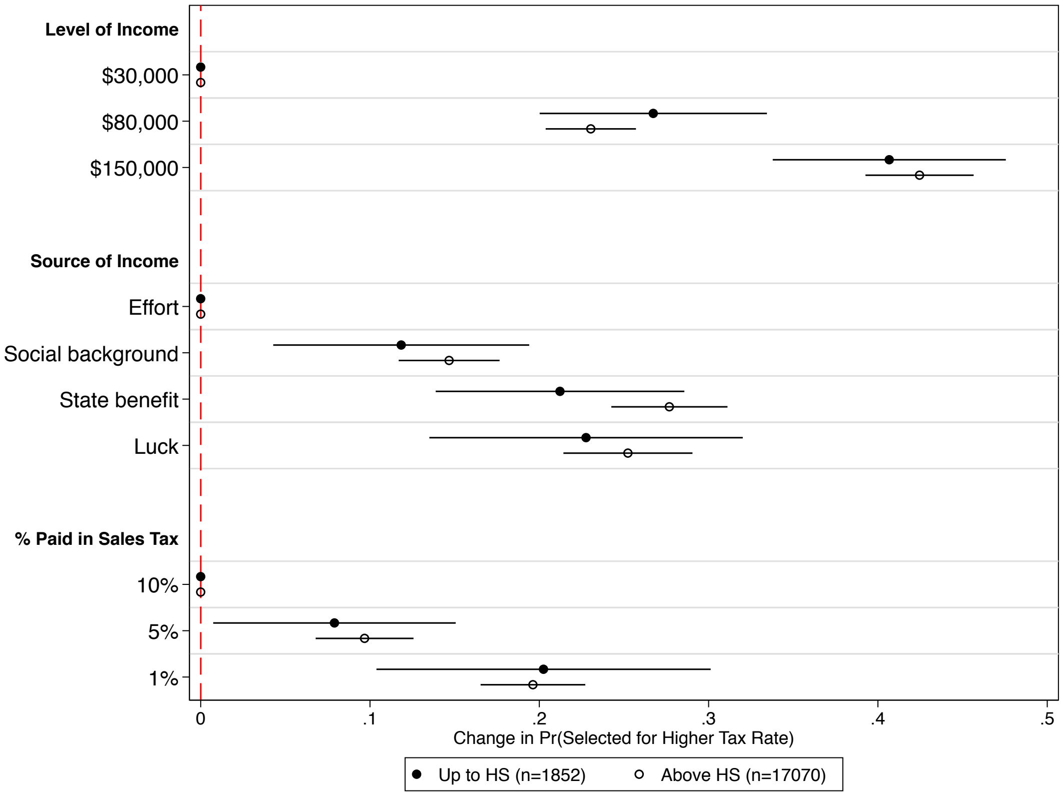
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two groups of respondents: whites and non-whites. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 46: Effect of Profile Attributes by Respondent Marital Status



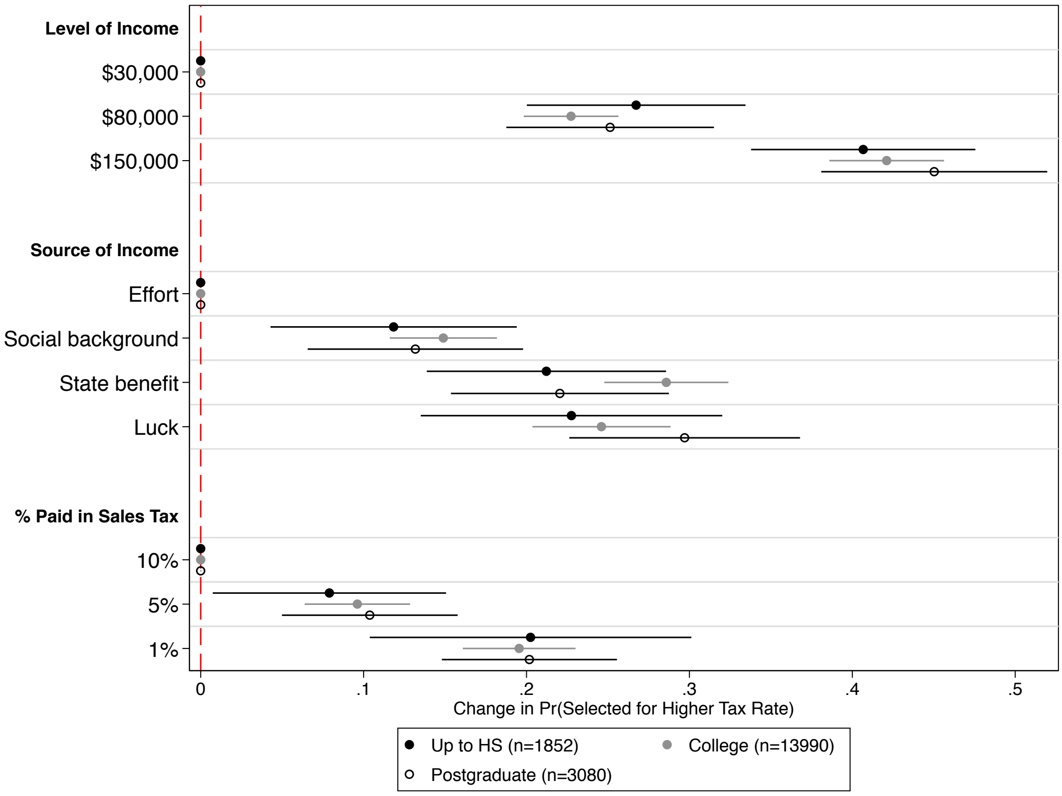
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two groups of respondents: those who are single and those who are or have been married. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 47: Effect of Profile Attributes by Respondent Level of Education: Low-High



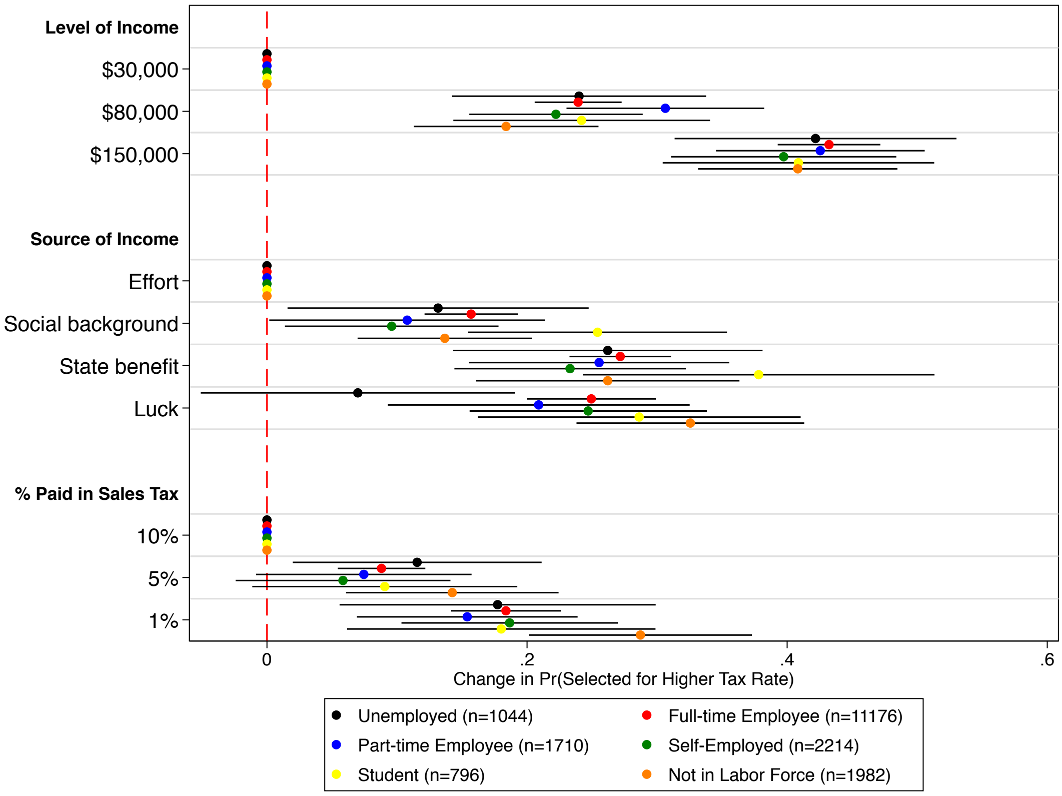
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: those with education up to high school and those with education above high school. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 48: Effect of Profile Attributes by Respondent Level of Education: Low-Medium-High



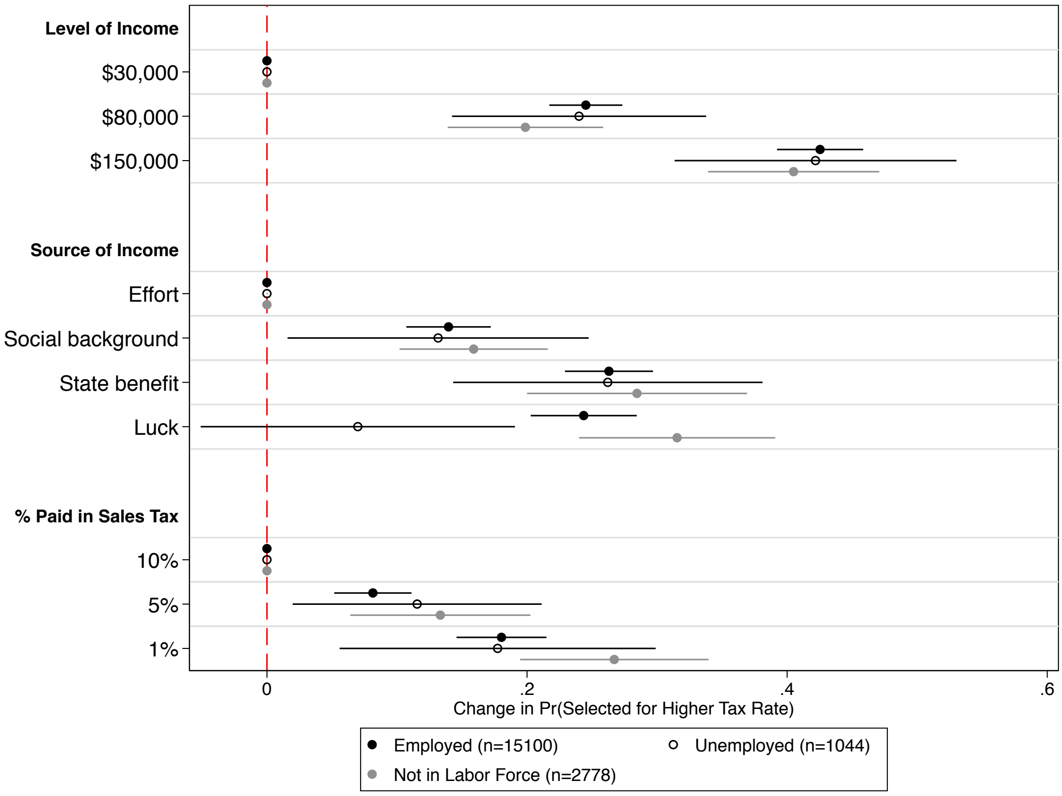
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of respondents: those with education up to high school, those with college education (at least some college, up to 4-year degree) and those with post-graduate education (MA, PhD or professional degree). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 49: Effect of Profile Attributes by Respondent Employment Status



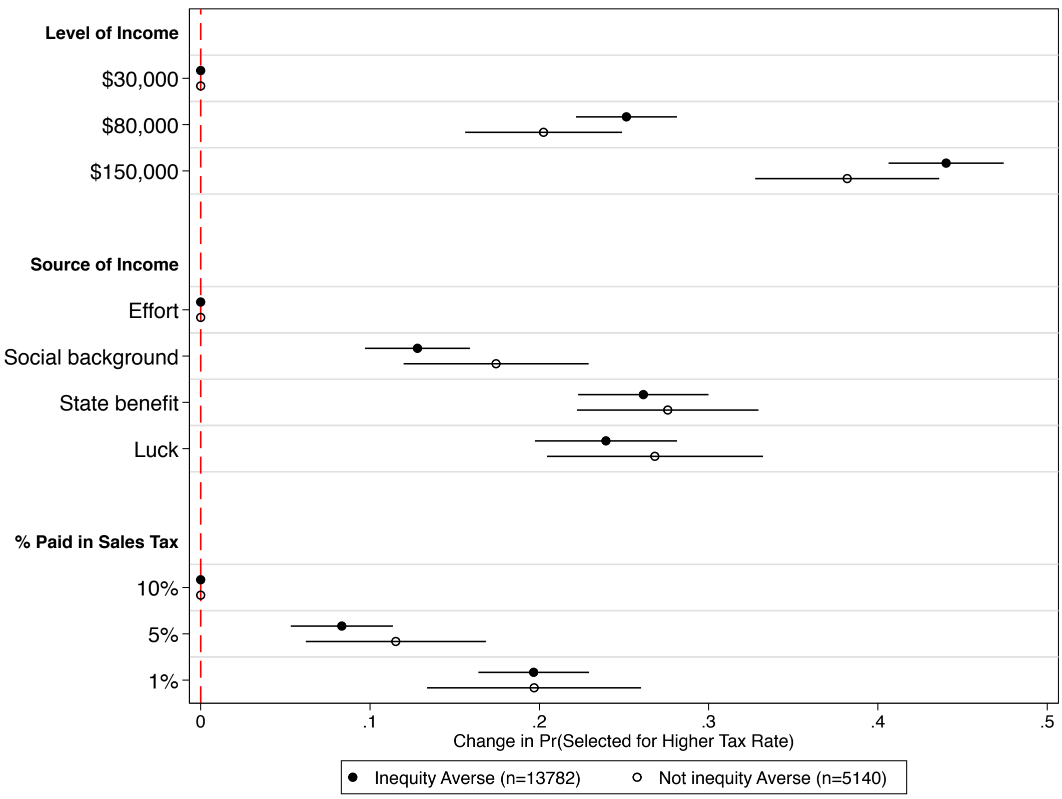
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for respondents grouped by their employment status. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 50: Effect of Profile Attributes by Groups of Respondent Employment Status



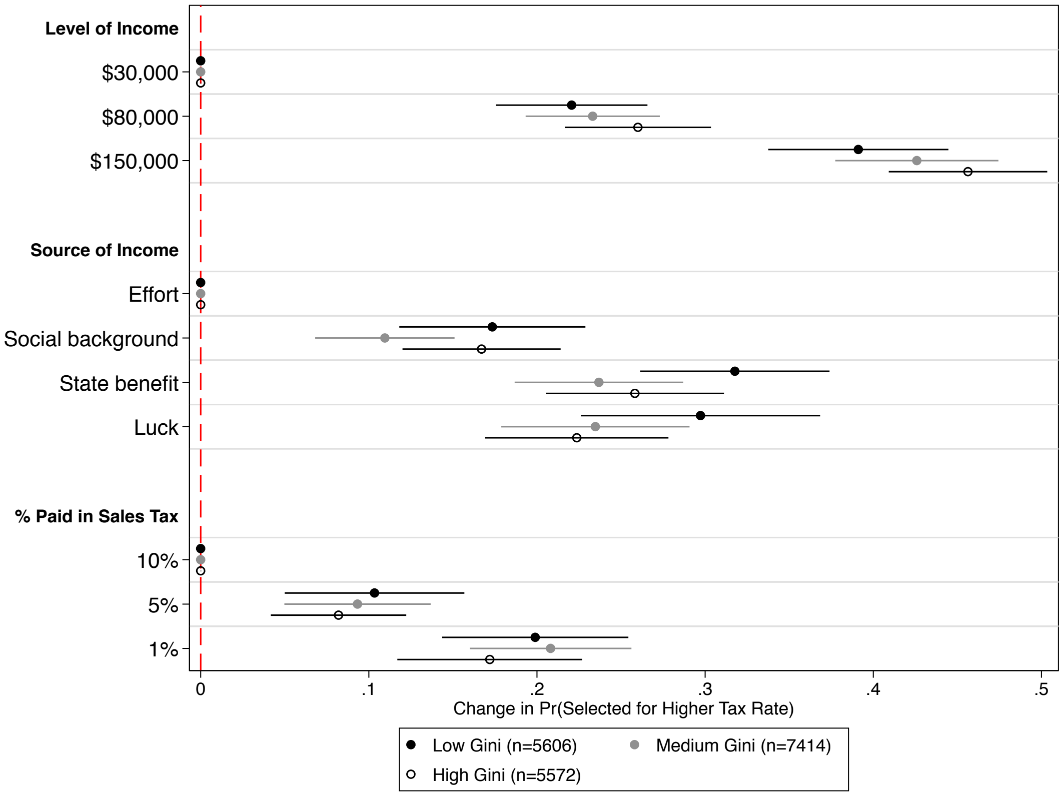
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of respondents: those employed (full, part-time or self-employed), those unemployed and those not in the labor force (including students). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 51: Effect of Profile Attributes by Respondent Inequality Aversion



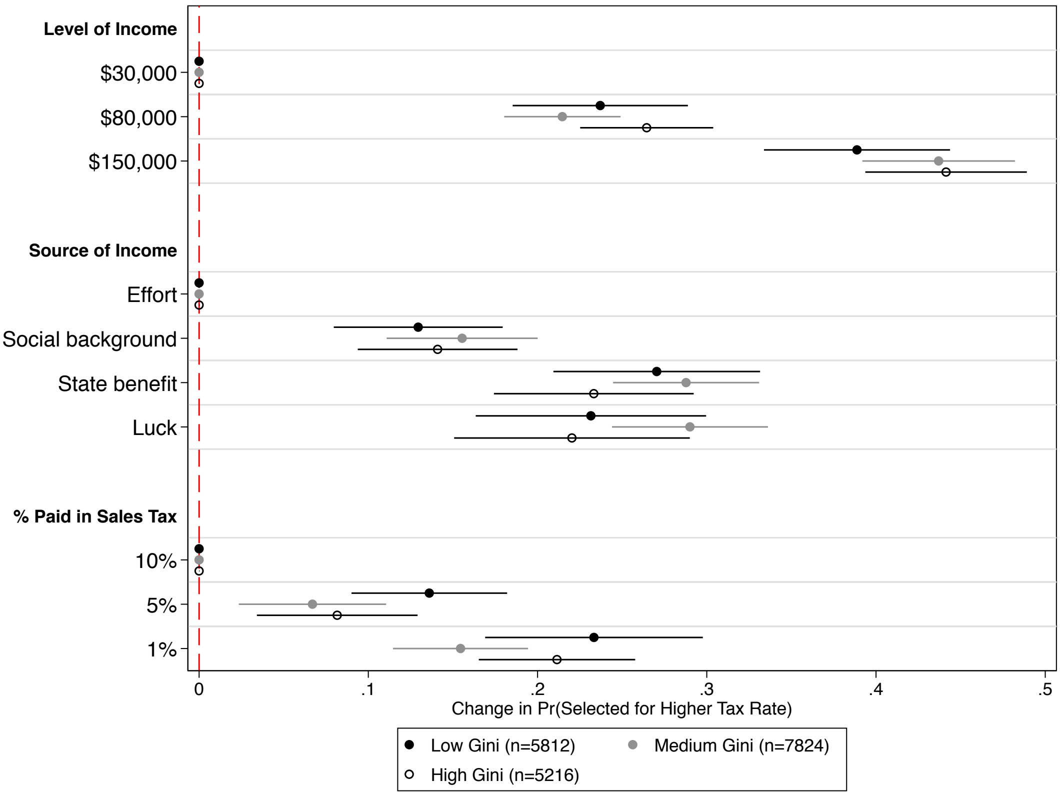
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: those who think current levels of inequality are too high (inequality averse), and those who think they are either too small or about right (not inequality averse). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 52: Effect of Profile Attributes by Respondent Zip Code-Level Inequality



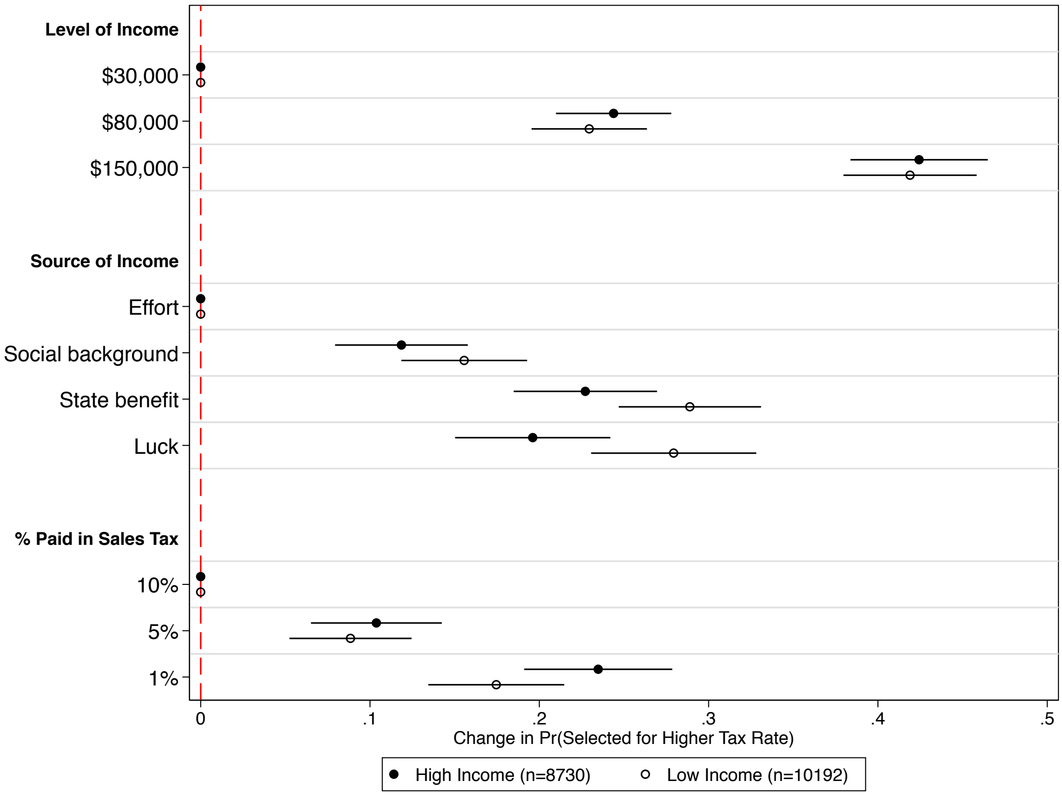
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of respondents: those living in zip codes with low (deciles 1-3 in the sample), medium (deciles 4-7) and high (deciles 8-10) levels of inequality. The points without horizontal bars denote the attribute value that is the reference category for each attribute. Zip-code level inequality data comes from the 2011-2015 American Community Survey 5-year estimates.

Figure 53: Effect of Profile Attributes by Respondent State-Level Inequality



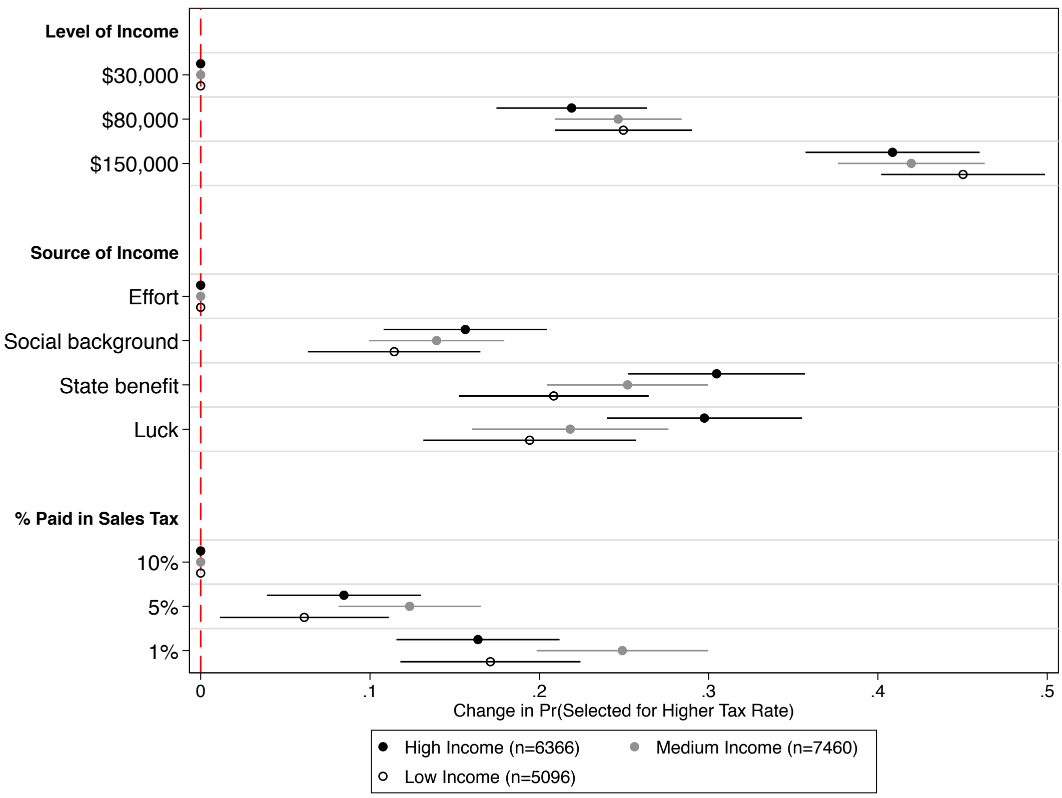
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of respondents: those living in states with low (deciles 1-3 in the sample), medium (deciles 4-7) and high (deciles 8-10) levels of inequality. The points without horizontal bars denote the attribute value that is the reference category for each attribute. State-level inequality data comes from the 2016 American Community Survey 1-year estimates.

Figure 54: Effect of Profile Attributes by Respondent Income Level: Low-High



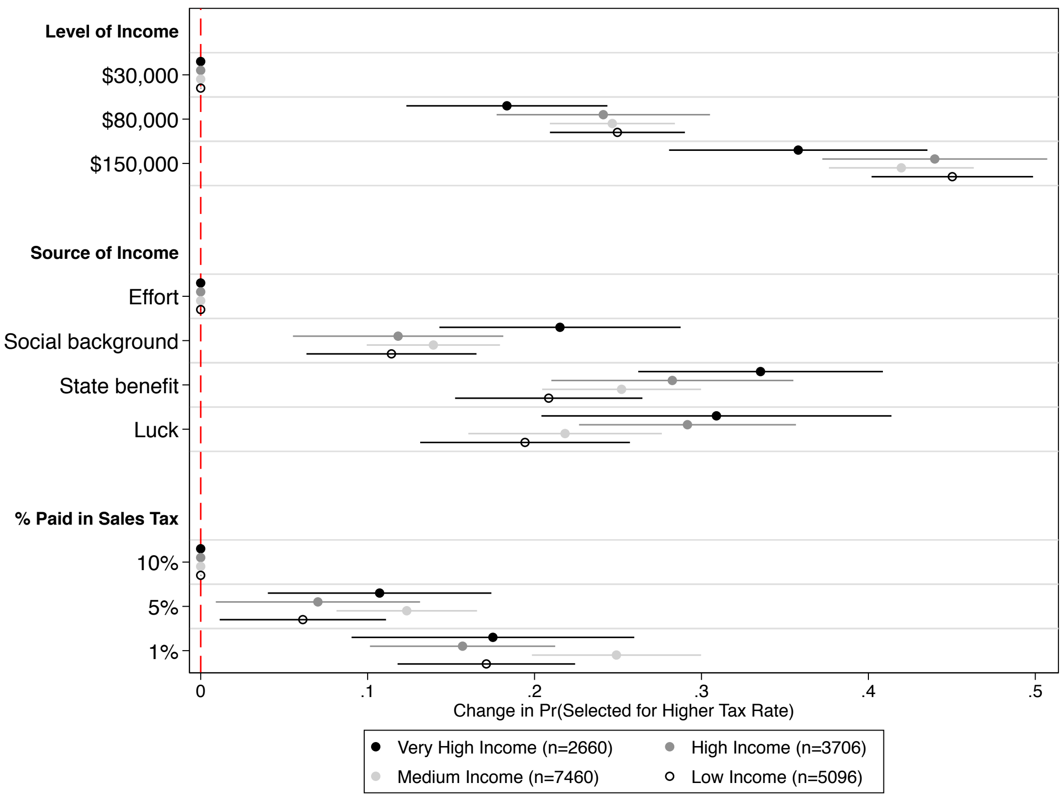
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: those with annual incomes below the sample median ($50,000 to $79,999) and including and above the sample median. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 55: Effect of Profile Attributes by Respondent Income Level: Low-Medium-High



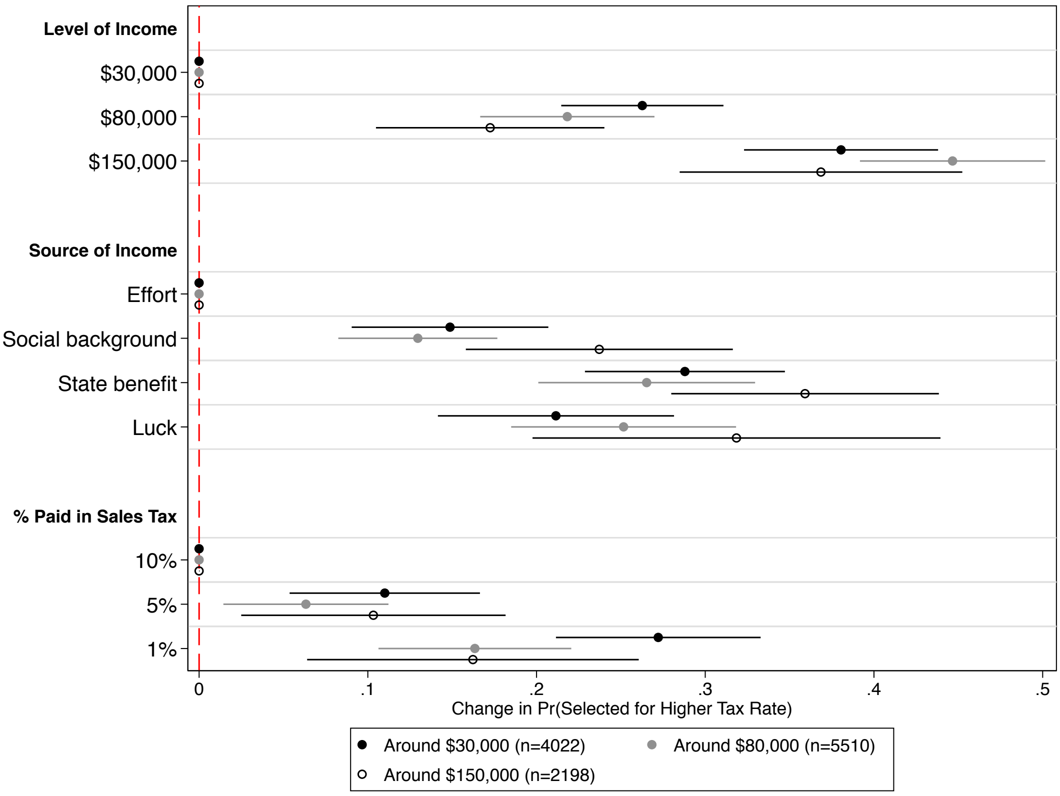
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of respondents: those with annual incomes up to $29,999 (low), between $30,000 and $79,999 (medium), and above $80,000 (high). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 56: Effect of Profile Attributes by Respondent Income Level: Low-Medium-High-Very High



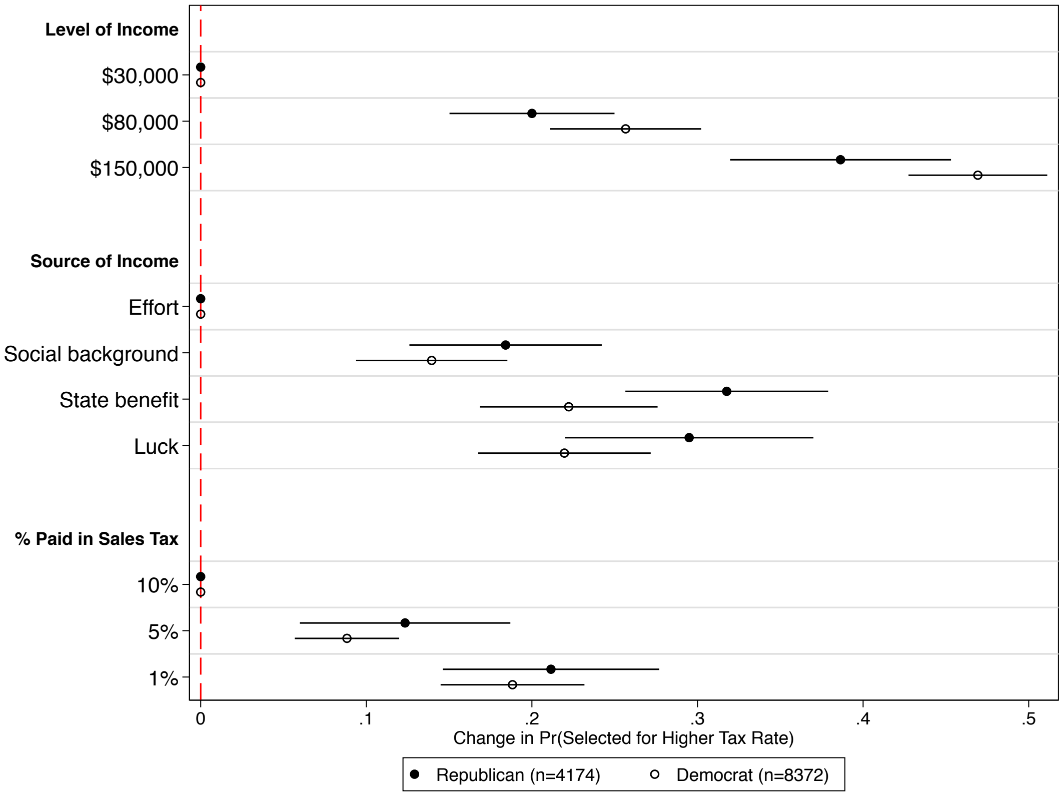
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for four different groups of respondents: those with annual incomes of $125,000 or above (very high income), between $80,000 and $124,999 (high income), between $30,000 and $79,999 (medium income), and under $30,000 (low income). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 57: Effect of Profile Attributes by Margins of Respondent Income



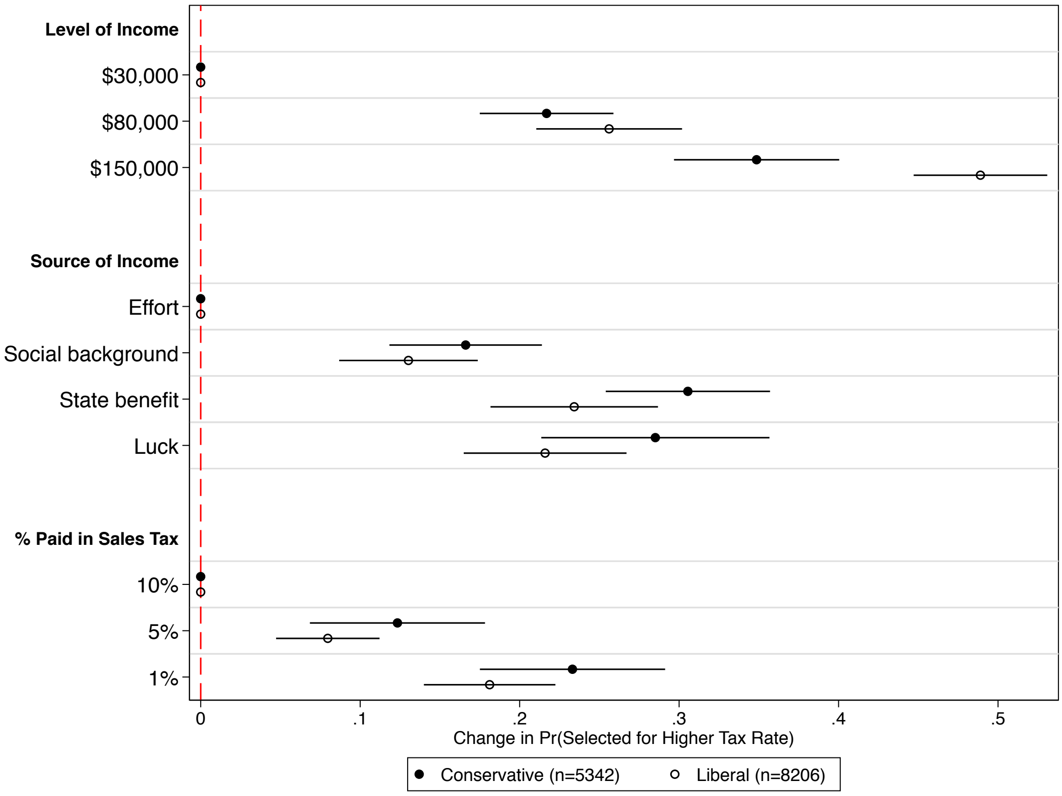
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of respondents: those with annual incomes between $20,000 and $39,999 (around $30,000), between $50,000 and $99,999 (around $80,000), and between $125,000 and $199,999 (around $150,000). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 58: Effect of Profile Attributes by Respondent Party Identification



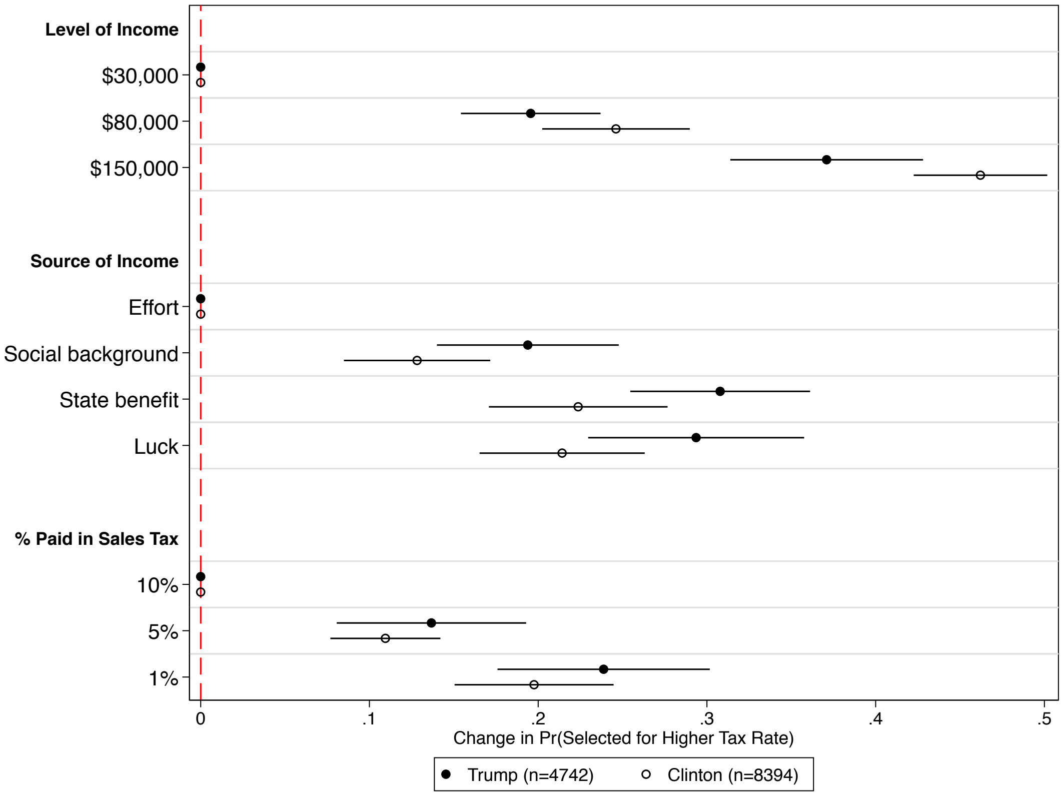
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: those who identify as Republicans, and those who identify as Democrats. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 59: Effect of Profile Attributes by Respondent Ideology



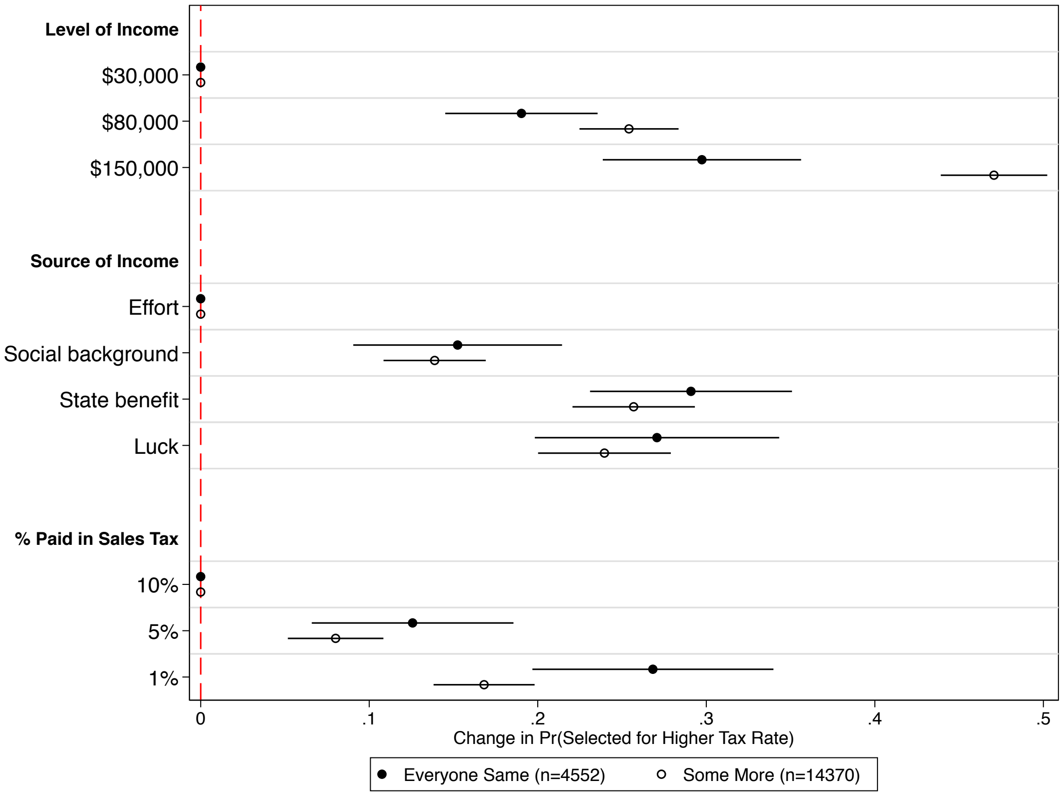
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: conservatives and liberals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 60: Effect of Profile Attributes by Respondent 2016 Vote Choice



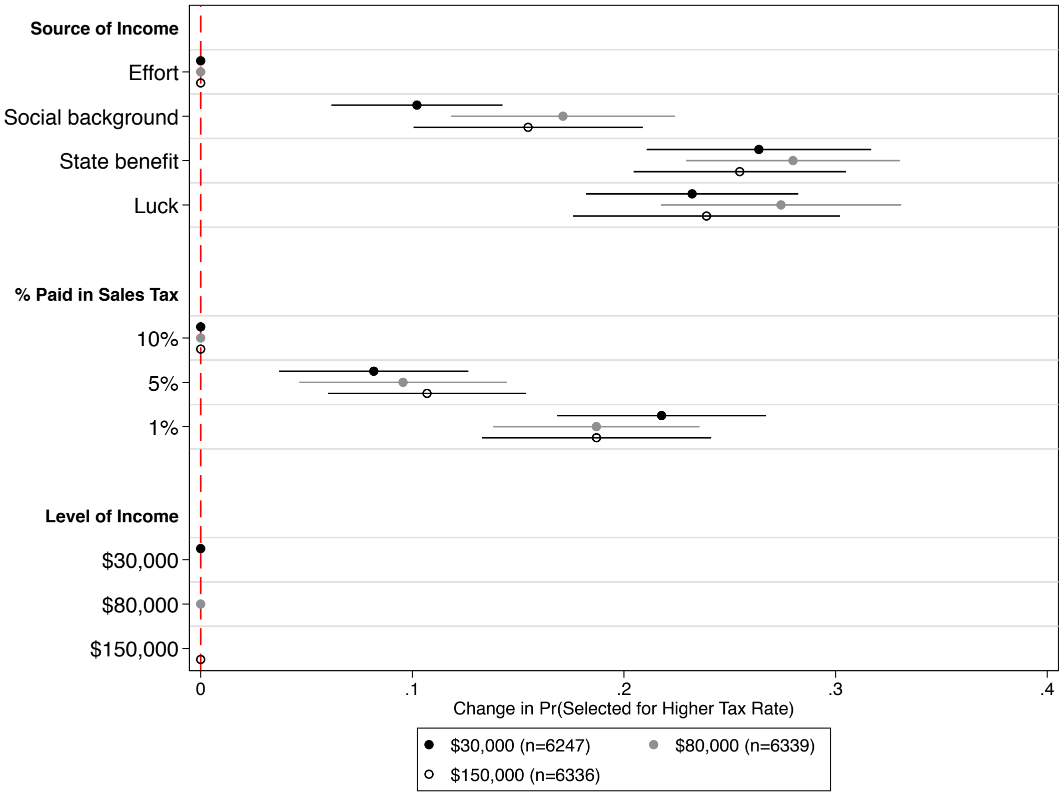
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two groups of respondents: those who voted for Trump and those who voted for Clinton in the 2016 presidential election. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 61: Effect of Profile Attributes by Respondent Adherence to Equal Treatment



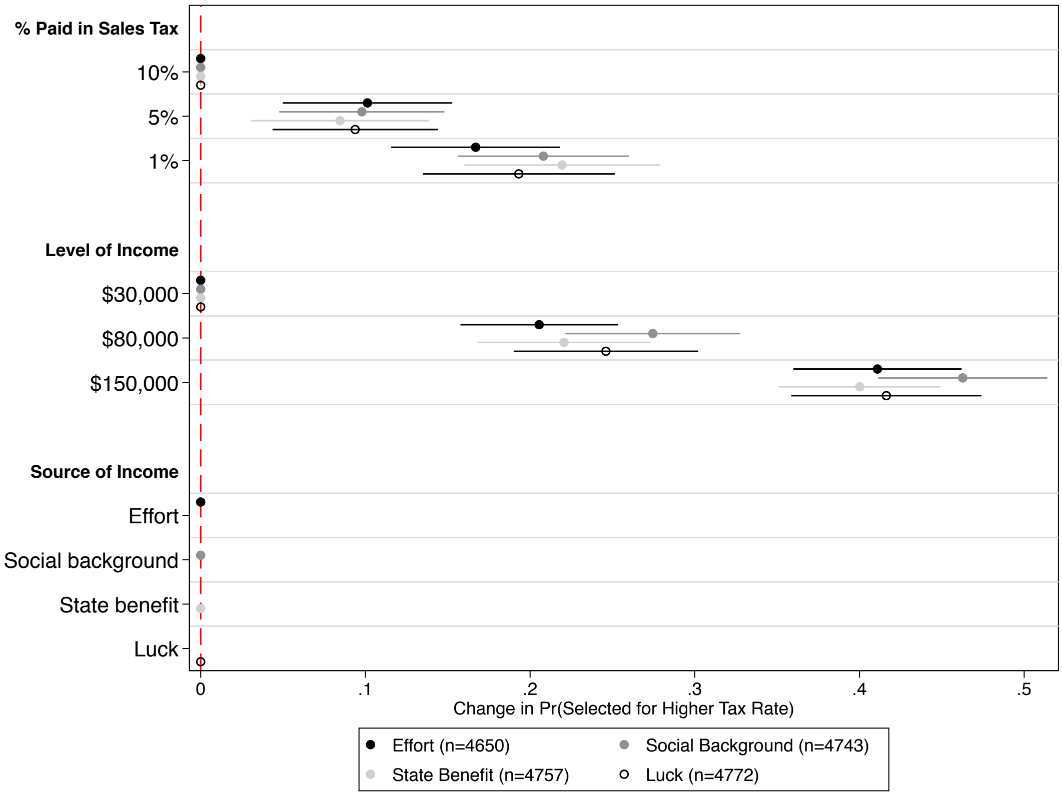
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for two different groups of respondents: those who think everyone should pay the same share of their income in taxes, and those who think some people should pay more than others. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 62: Effect of Profile Attributes by Level of Income in Profile



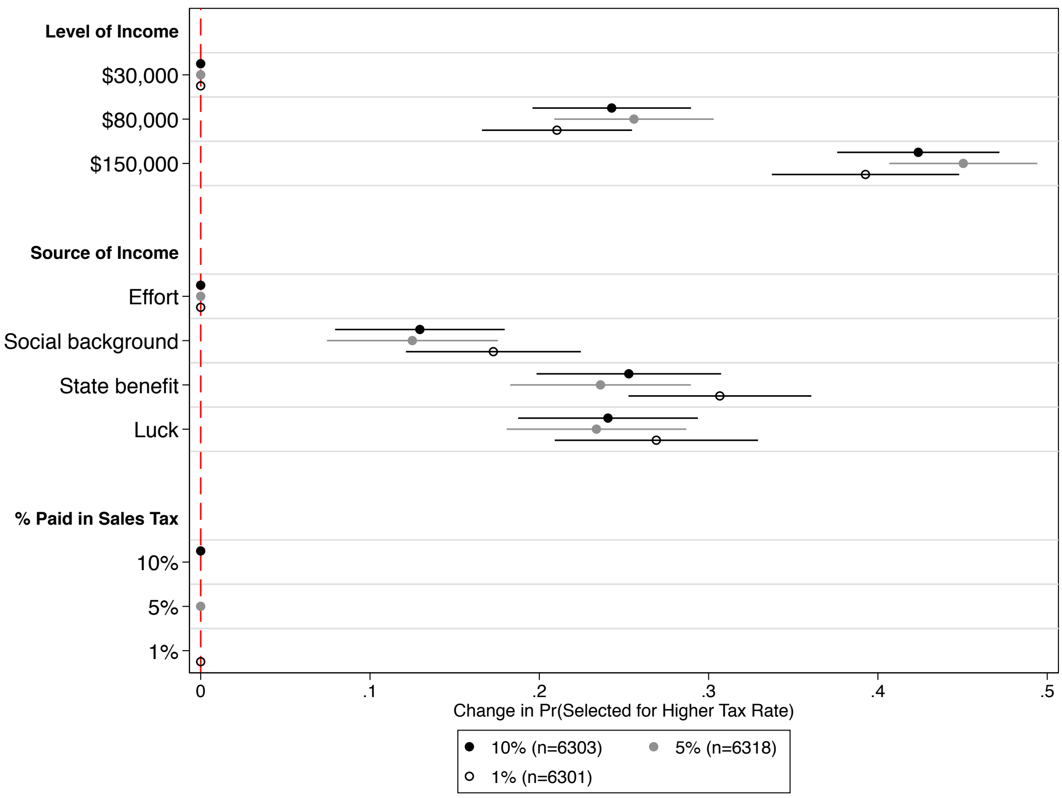
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of profiles: those with income level $30,000, those with income level $80,000 and those with income level $150,000. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 63: Effect of Profile Attributes by Source of Income in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for four different groups of profiles: those with source of income "Started own small business" (effort), those with source of income "Got a job through family connections" (social background), those with source of income "Owns business that was bailed out by the government" (state benefit), and those with source of income "Receives annuity from lottery prize" (luck). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

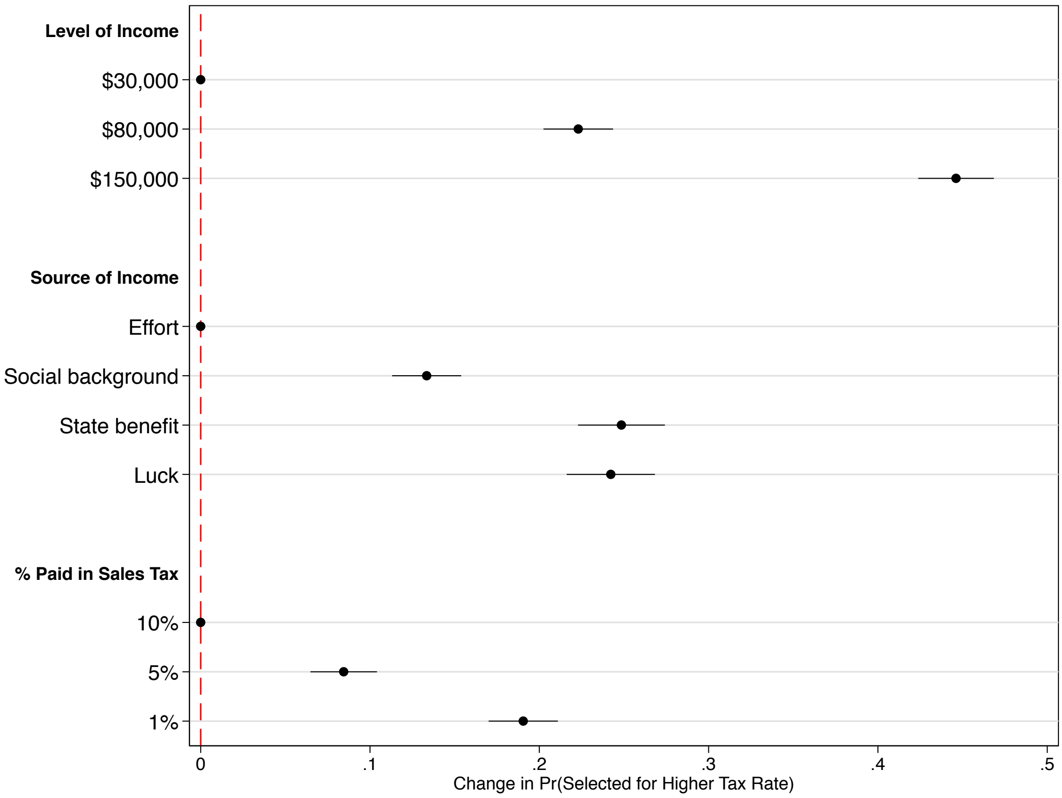
Figure 64: Effect of Profile Attributes by Share of Income Paid in Sales Tax in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent and post-stratification weights, estimated for three different groups of profiles: those with percentage of income paid in sales tax of 1, 5 and 10%. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

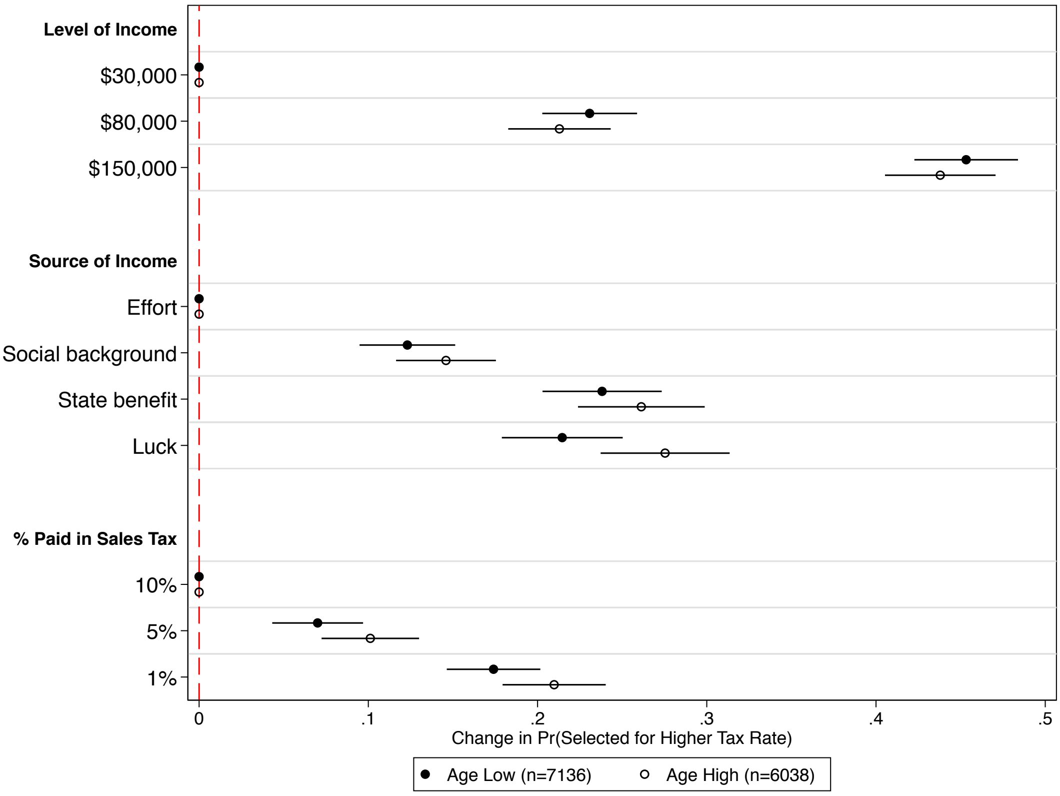
A.6 Results Excluding Atypical Profiles

Figure 65: Effect of Profile Attributes on Probability of Being Selected for Higher Tax Rate



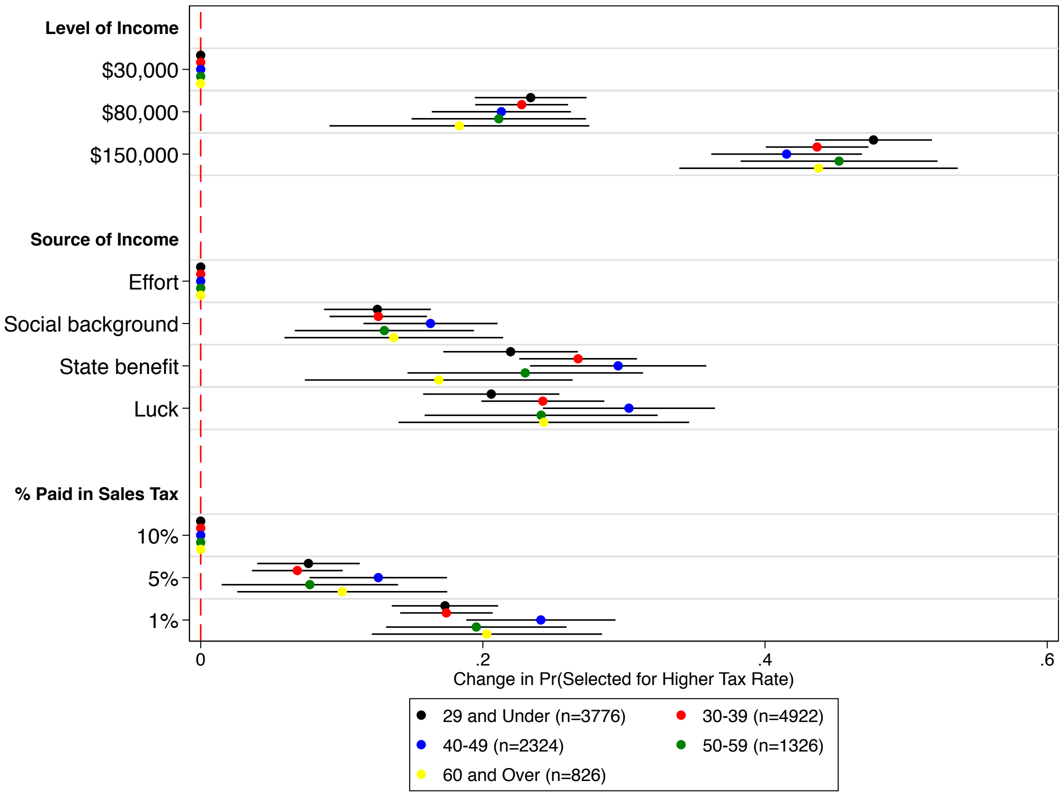
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile. Bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 66: Effect of Profile Attributes by Respondent Age



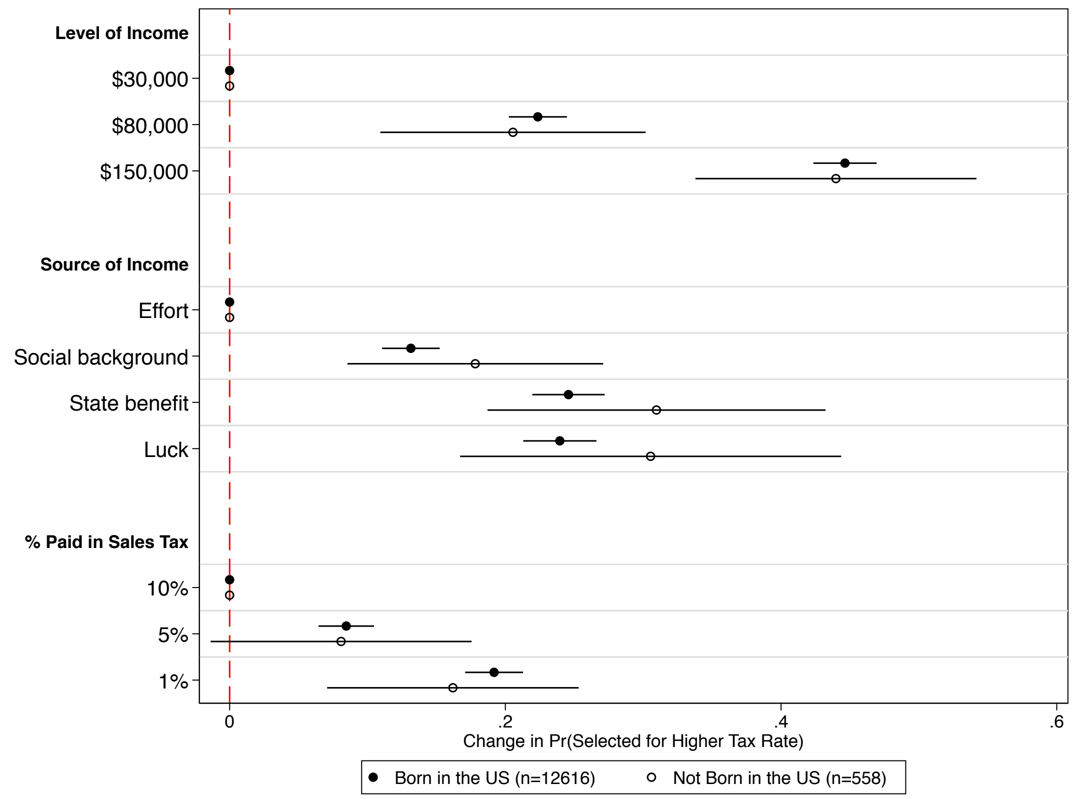
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: those with age above and below the median (35). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 67: Effect of Profile Attributes by Respondent Age Groups



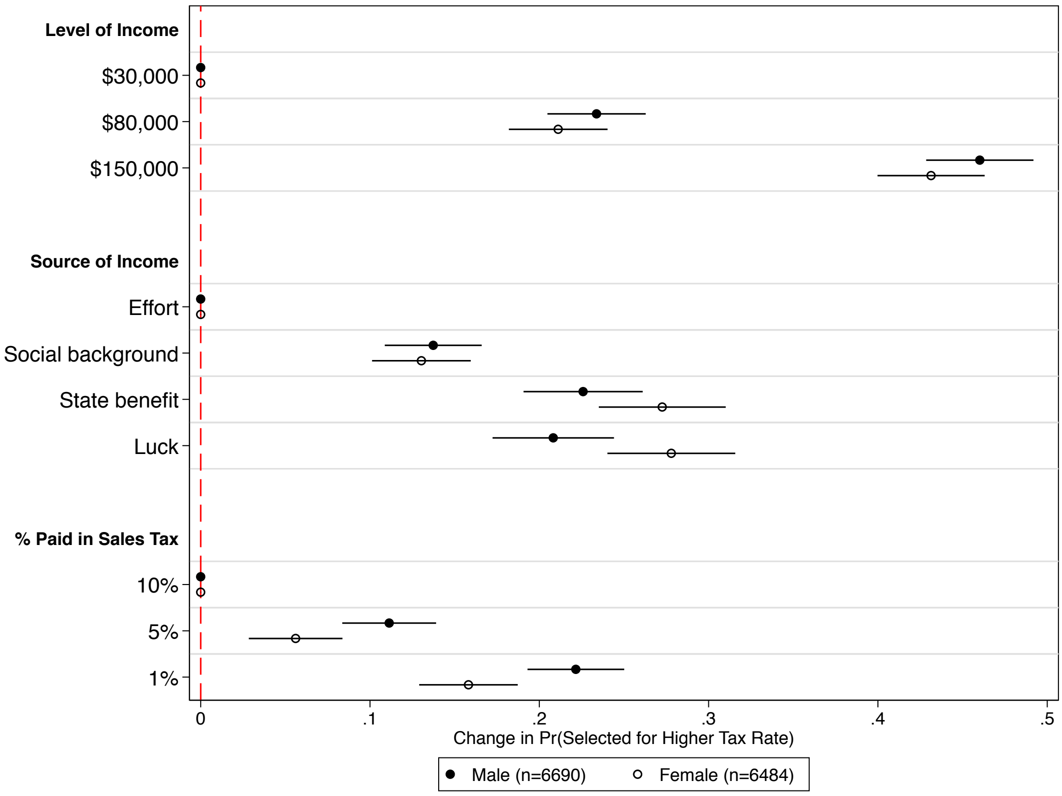
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for respondents grouped by their age. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 68: Effect of Profile Attributes by Respondent Place of Birth



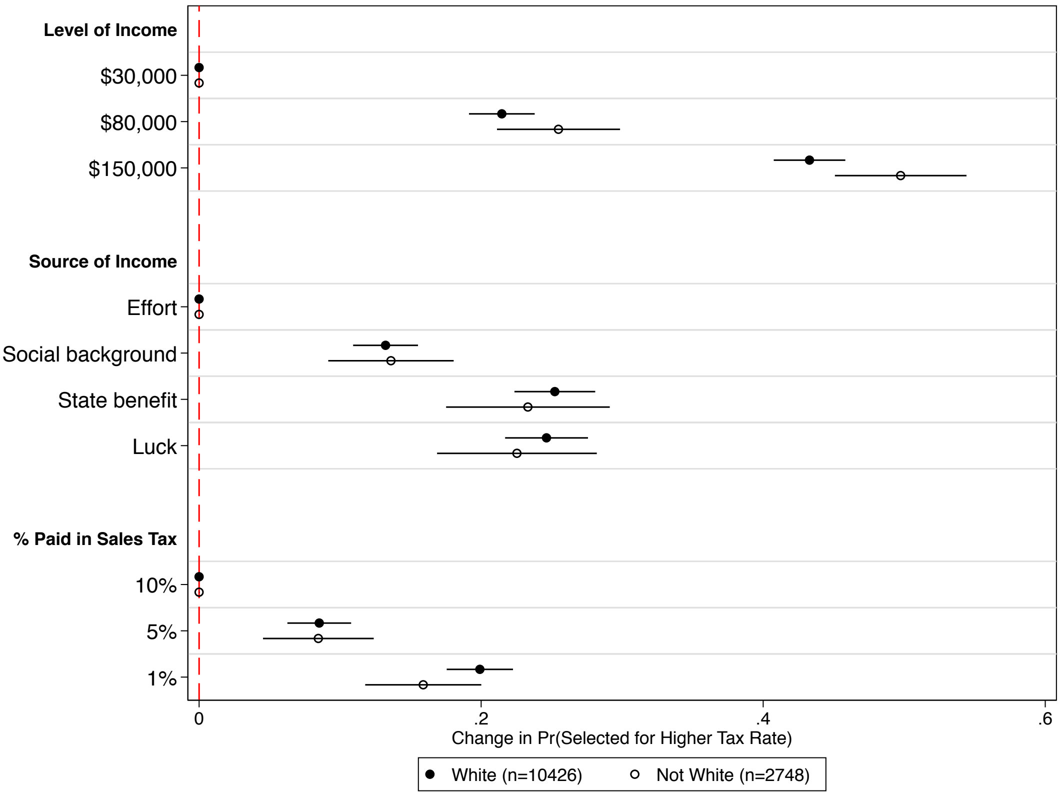
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for respondents grouped by their place of birth. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 69: Effect of Profile Attributes by Respondent Gender



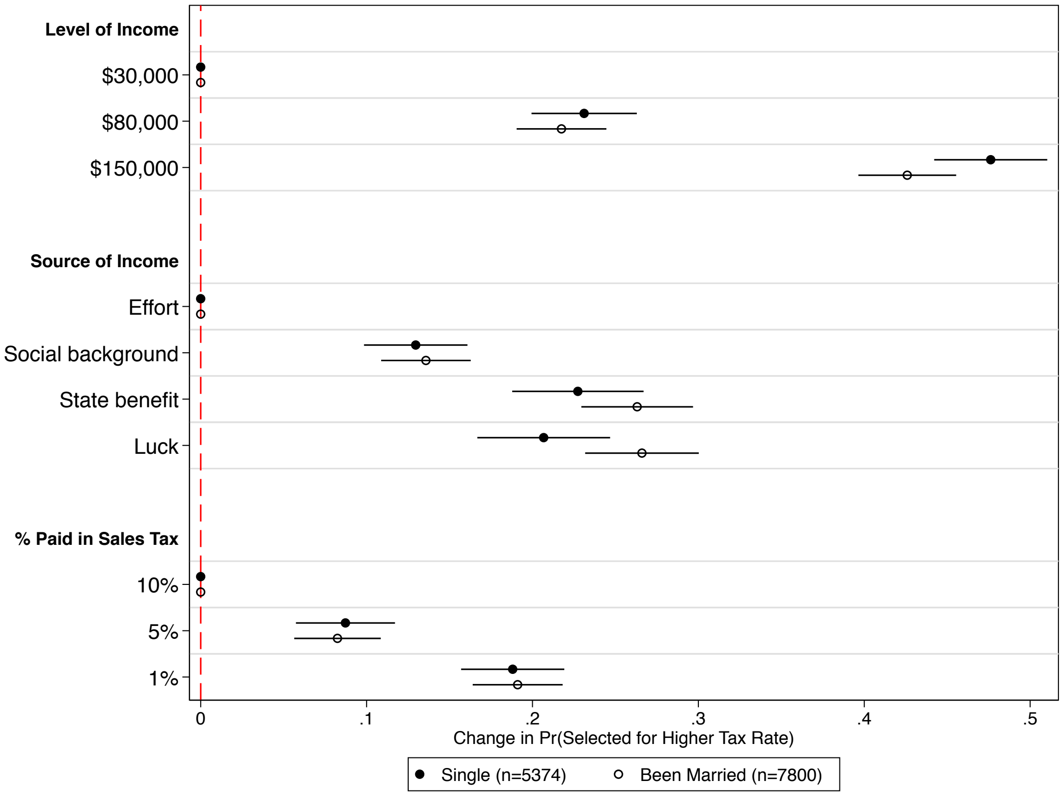
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for male and female respondents. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 70: Effect of Profile Attributes by Respondent Race



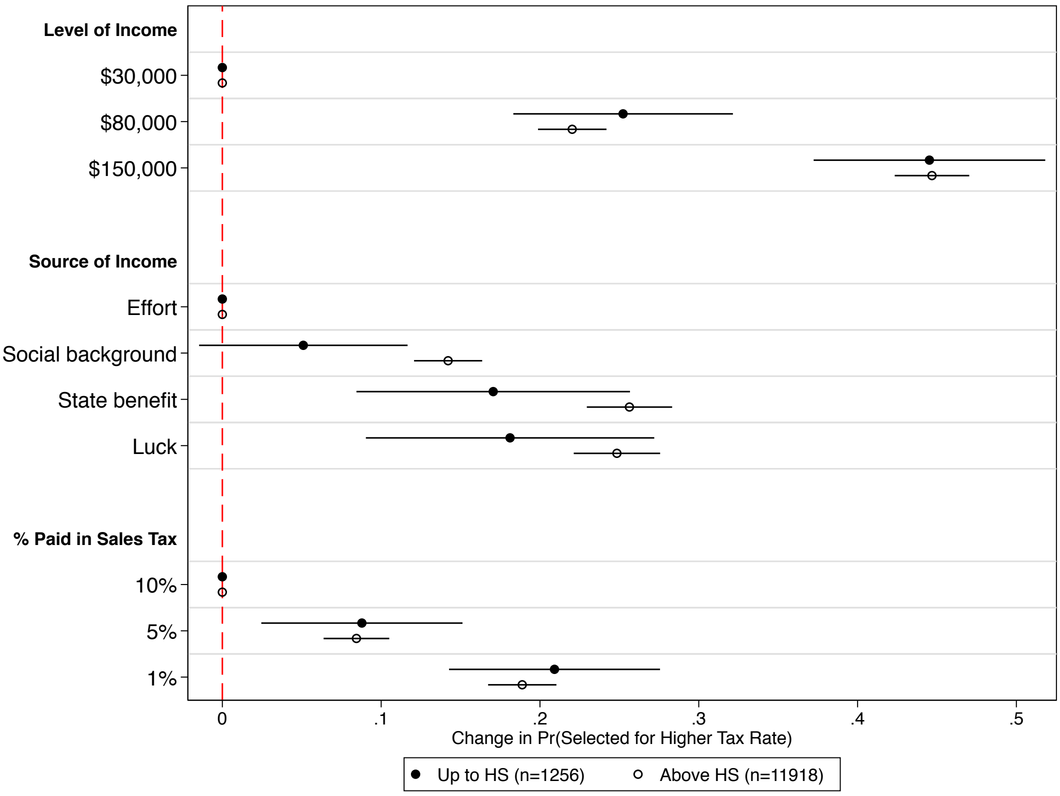
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two groups of respondents: whites and non-whites. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 71: Effect of Profile Attributes by Respondent Marital Status



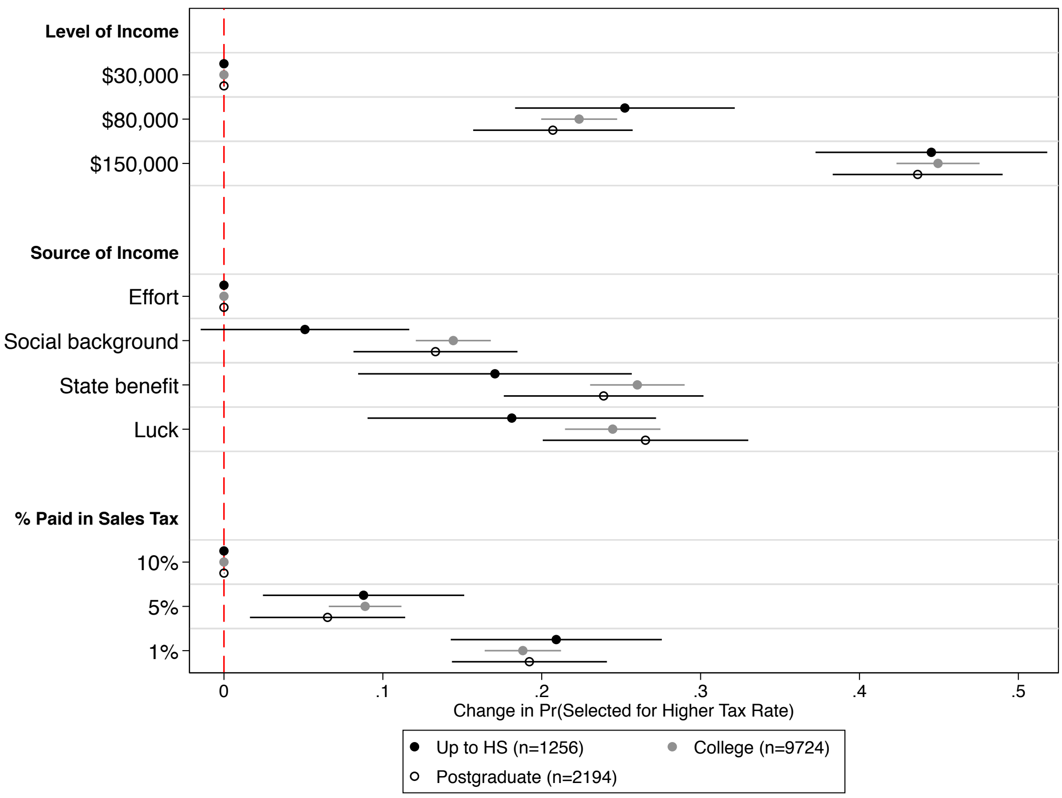
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two groups of respondents: those who are single and those who are or have been married. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 72: Effect of Profile Attributes by Respondent Level of Education: Low-High



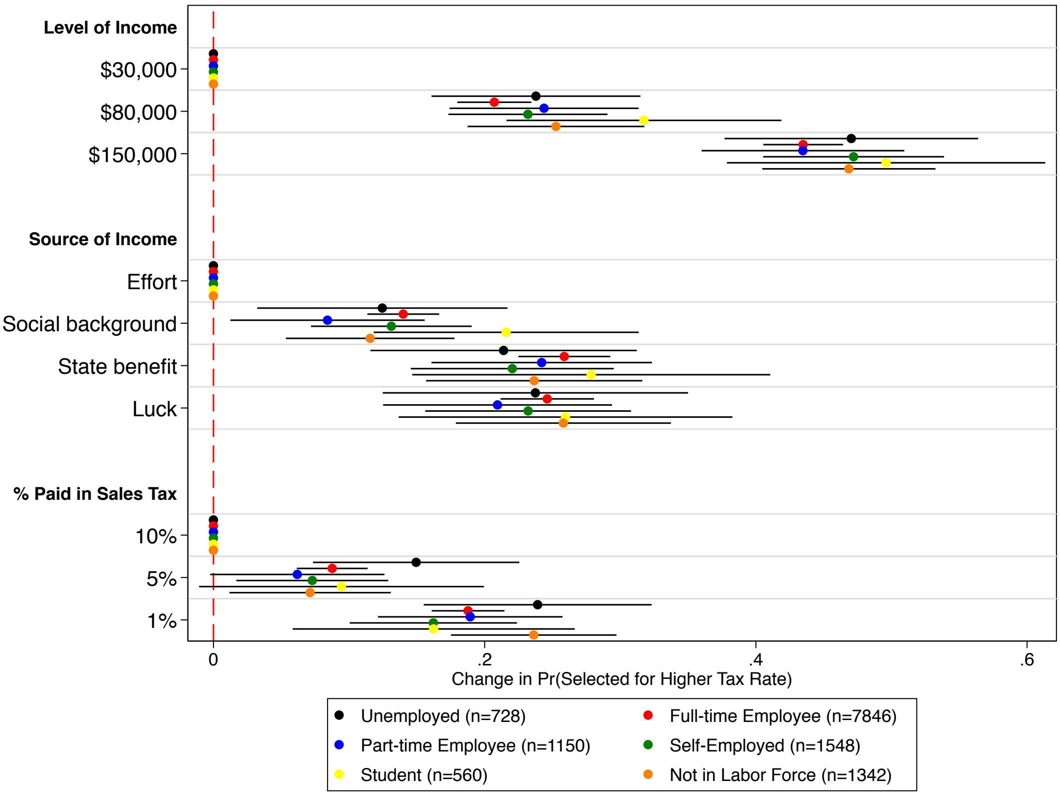
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: those with education up to high school and those with education above high school. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 73: Effect of Profile Attributes by Respondent Level of Education: Low-Medium-High



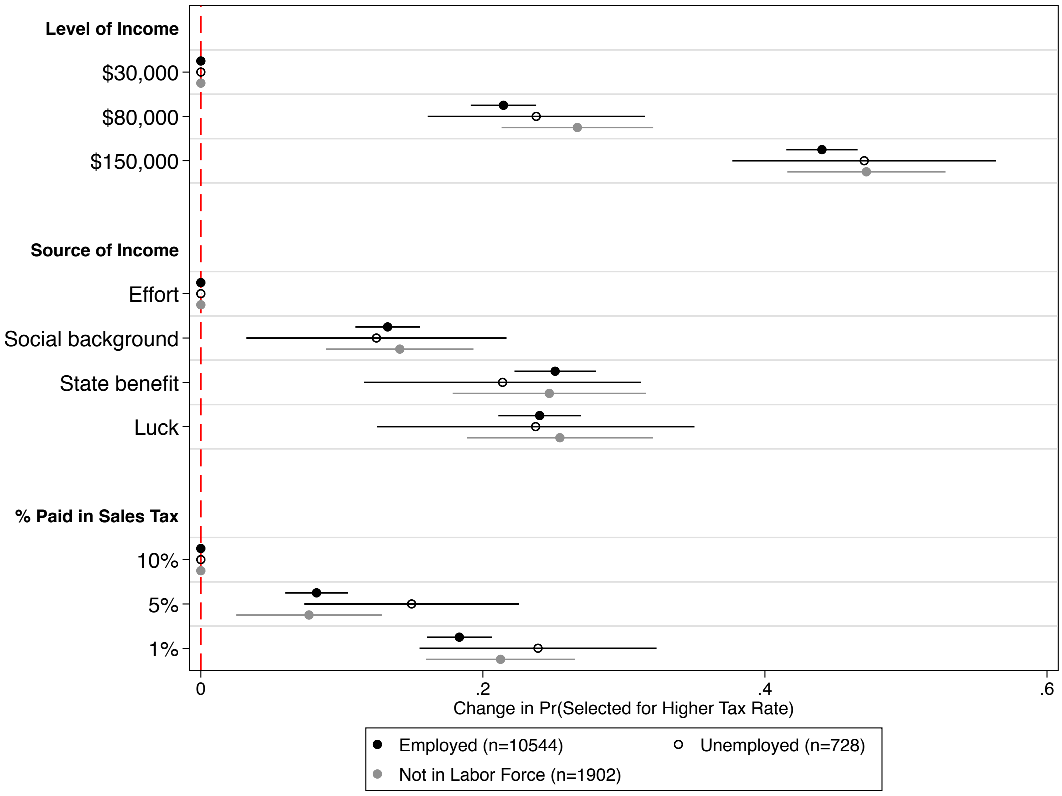
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of respondents: those with education up to high school, those with college education (at least some college, up to 4-year degree) and those with post-graduate education (MA, PhD or professional degree). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 74: Effect of Profile Attributes by Respondent Employment Status



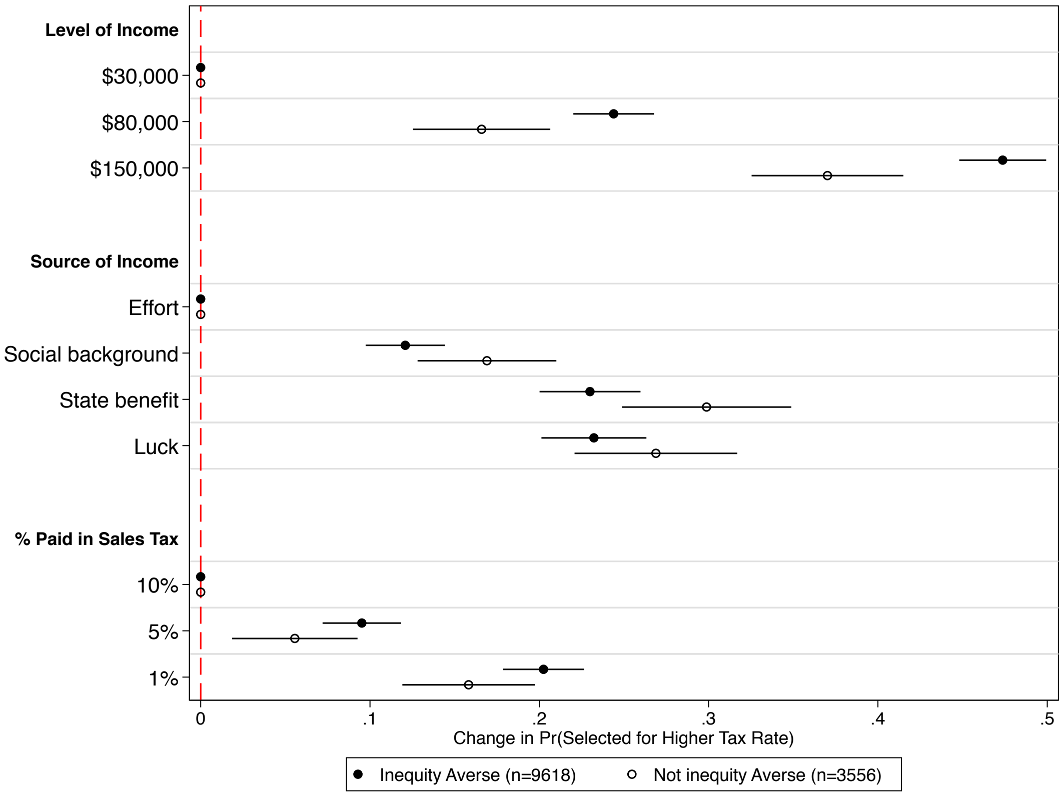
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for respondents grouped by their employment status. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 75: Effect of Profile Attributes by Groups of Respondent Employment Status



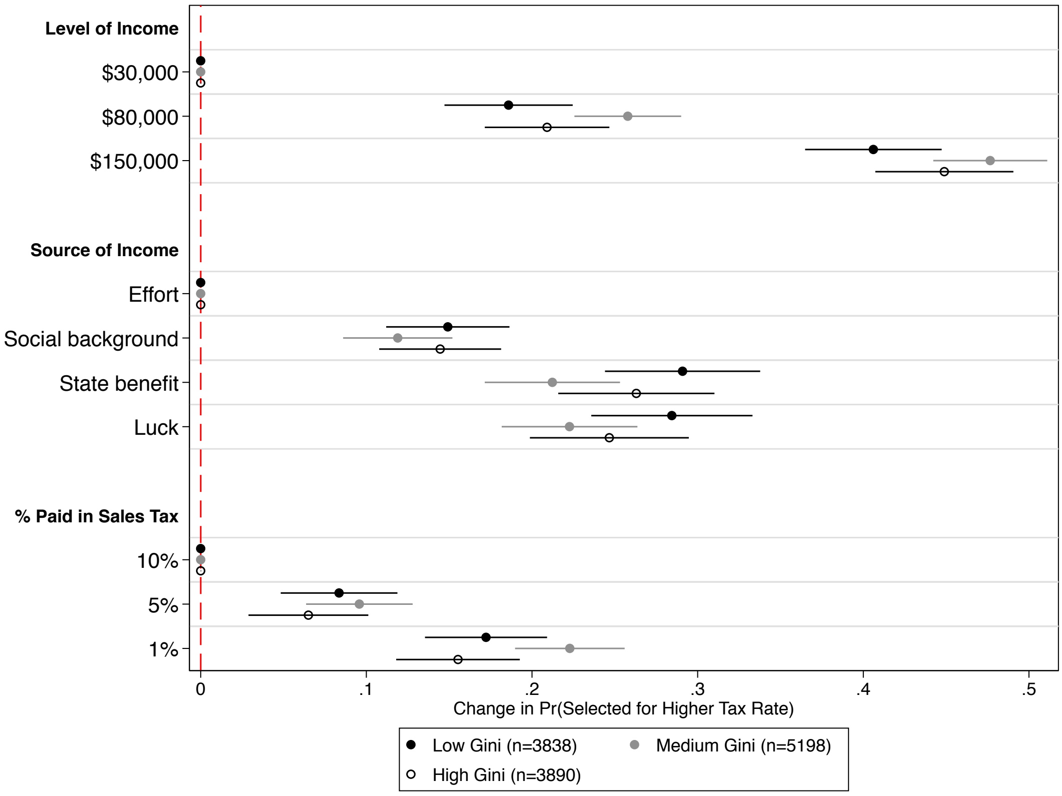
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of respondents: those employed (full, part-time or self-employed), those unemployed and those not in the labor force (including students). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 76: Effect of Profile Attributes by Respondent Inequality Aversion



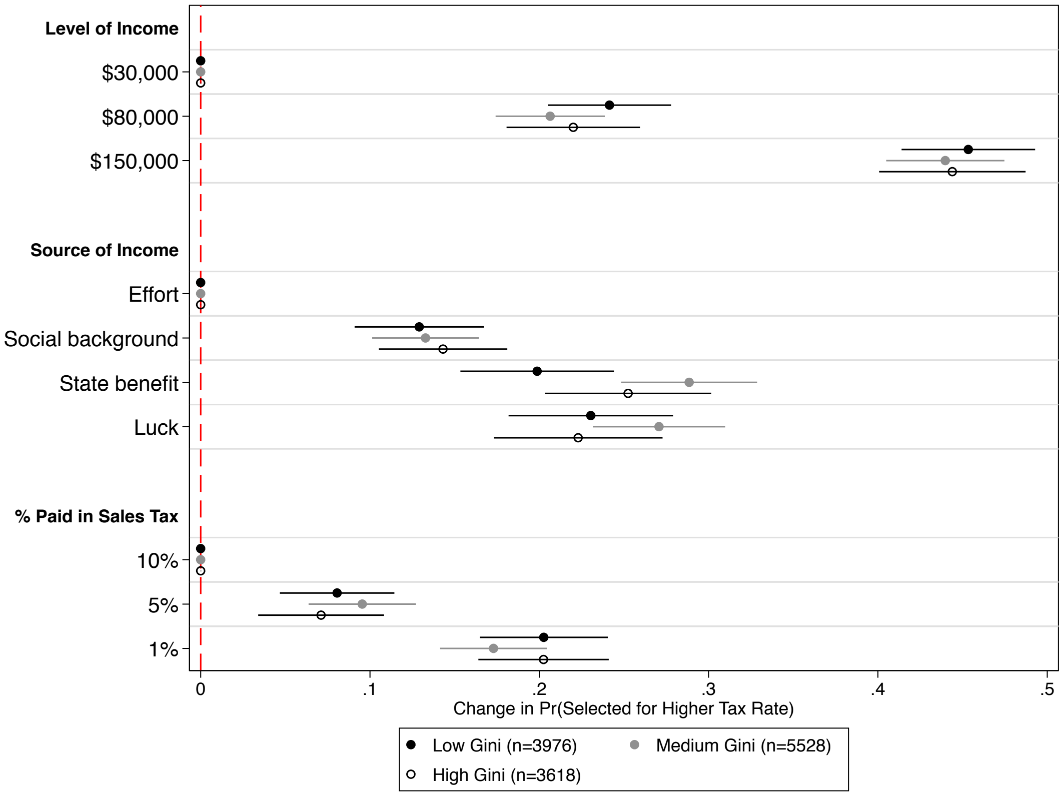
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: those who think current levels of inequality are too high (inequality averse), and those who think they are either too small or about right (not inequality averse). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 77: Effect of Profile Attributes by Respondent Zip Code-Level Inequality



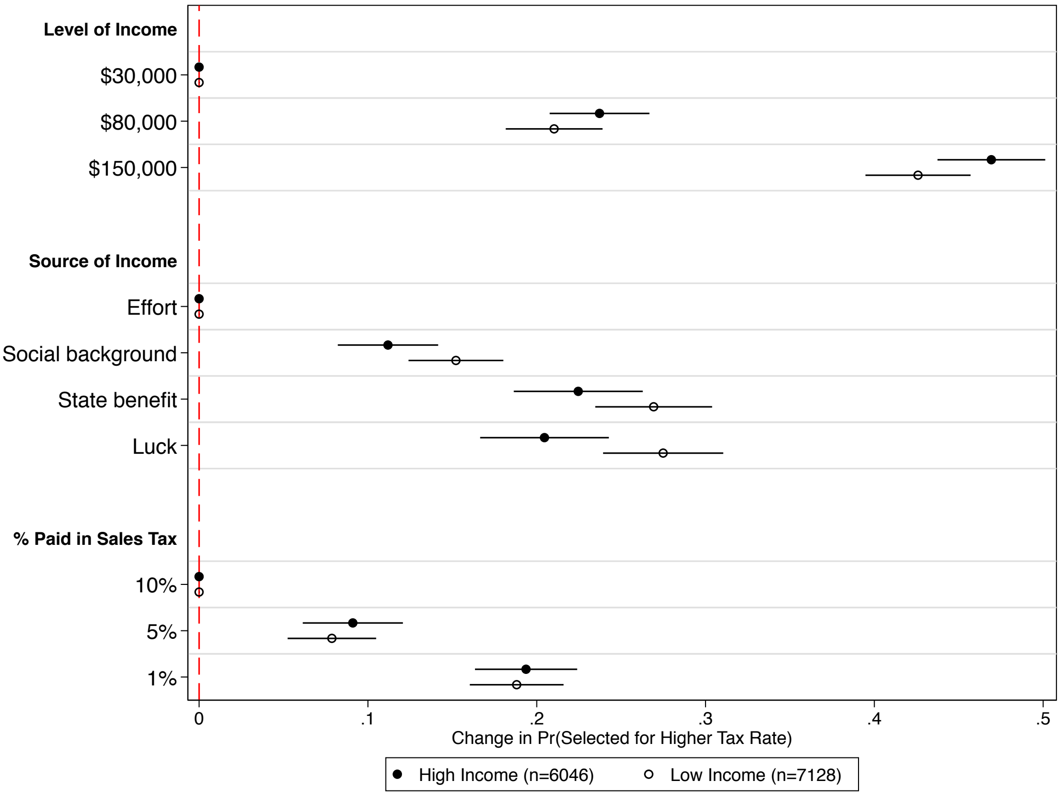
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of respondents: those living in zip codes with low (deciles 1-3 in the sample), medium (deciles 4-7) and high (deciles 8-10) levels of inequality. The points without horizontal bars denote the attribute value that is the reference category for each attribute. Zip-code level inequality data comes from the 2011-2015 American Community Survey 5-year estimates.

Figure 78: Effect of Profile Attributes by Respondent State-Level Inequality



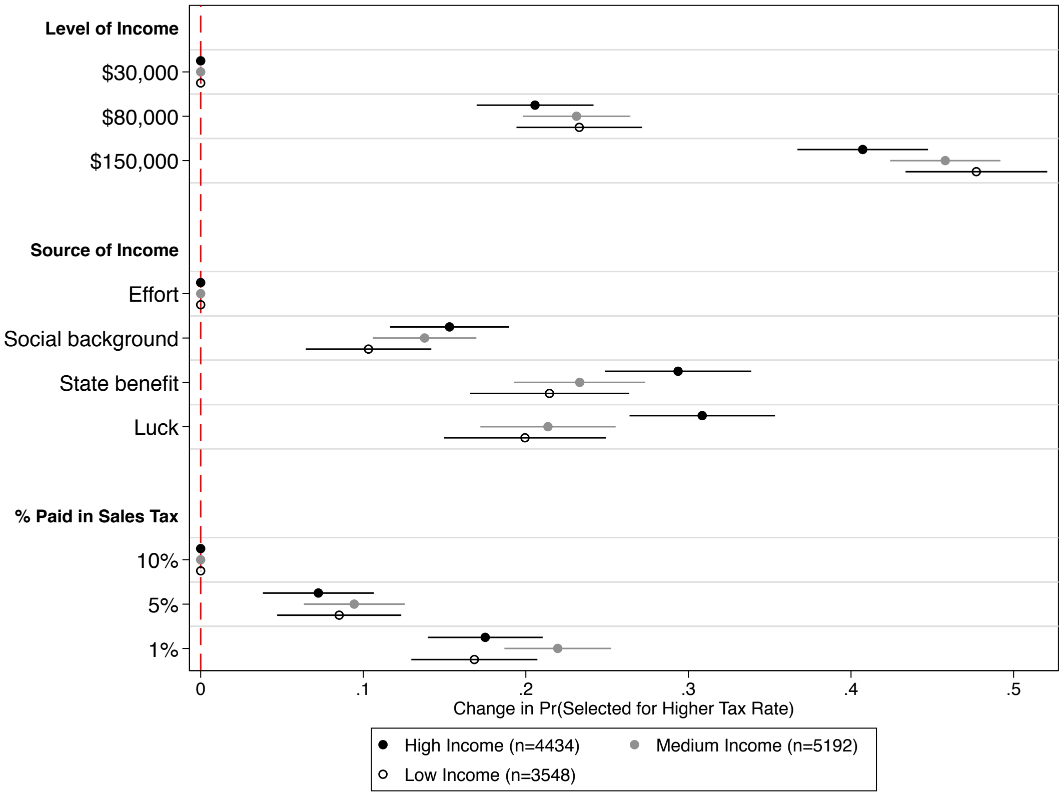
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of respondents: those living in states with low (deciles 1-3 in the sample), medium (deciles 4-7) and high (deciles 8-10) levels of inequality. The points without horizontal bars denote the attribute value that is the reference category for each attribute. State-level inequality data comes from the 2016 American Community Survey 1-year estimates.

Figure 79: Effect of Profile Attributes by Respondent Income Level: Low-High



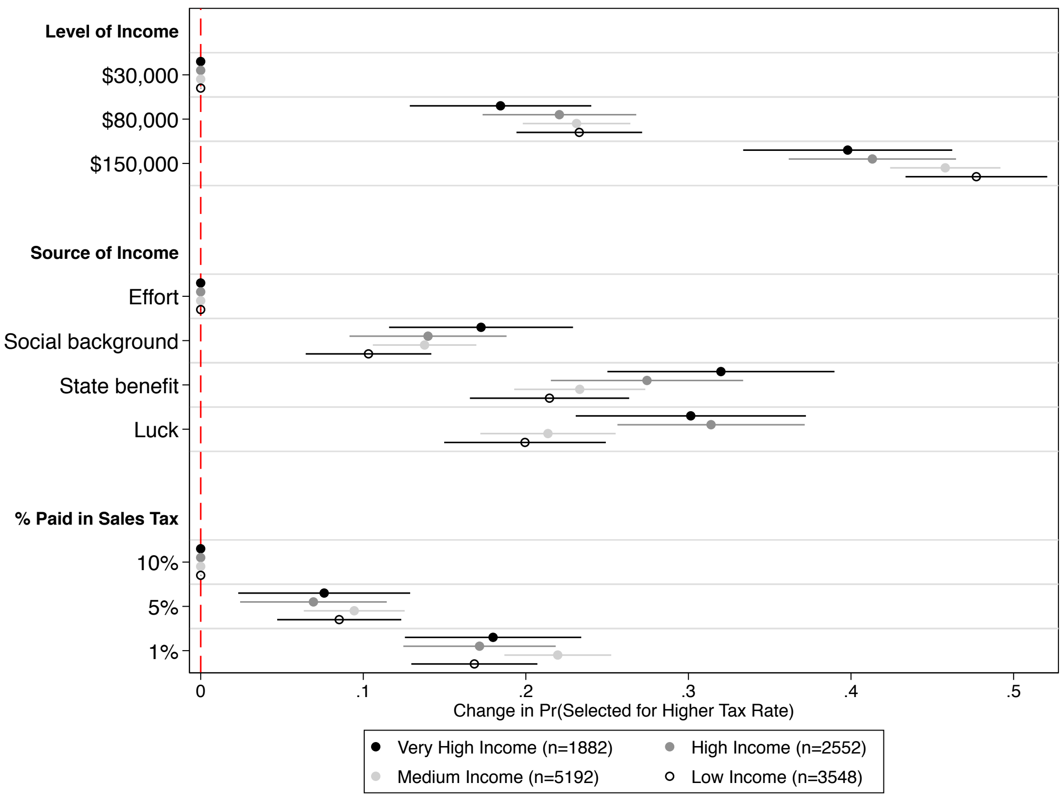
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: those with annual incomes below the sample median ($50,000 to $79,999) and including and above the sample median. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 80: Effect of Profile Attributes by Respondent Income Level: Low-Medium-High



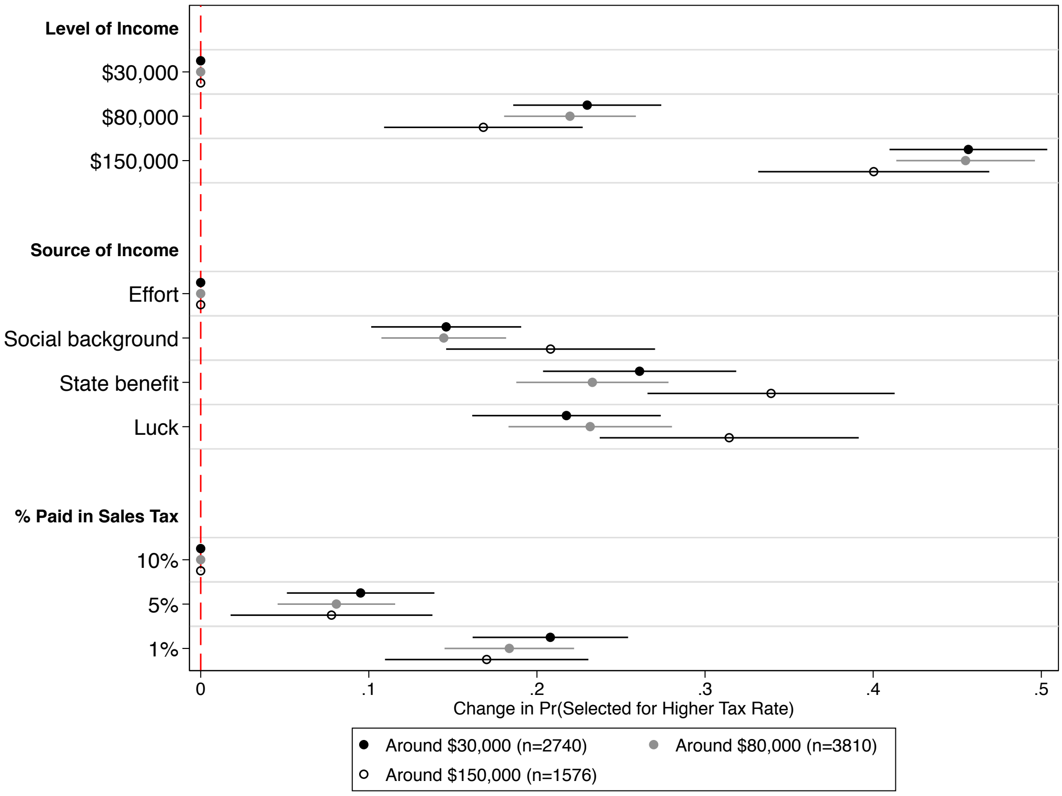
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of respondents: those with annual incomes up to $29,999 (low), between $30,000 and $79,999 (medium), and above $80,000 (high). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 81: Effect of Profile Attributes by Respondent Income Level: Low-Medium-High-Very High



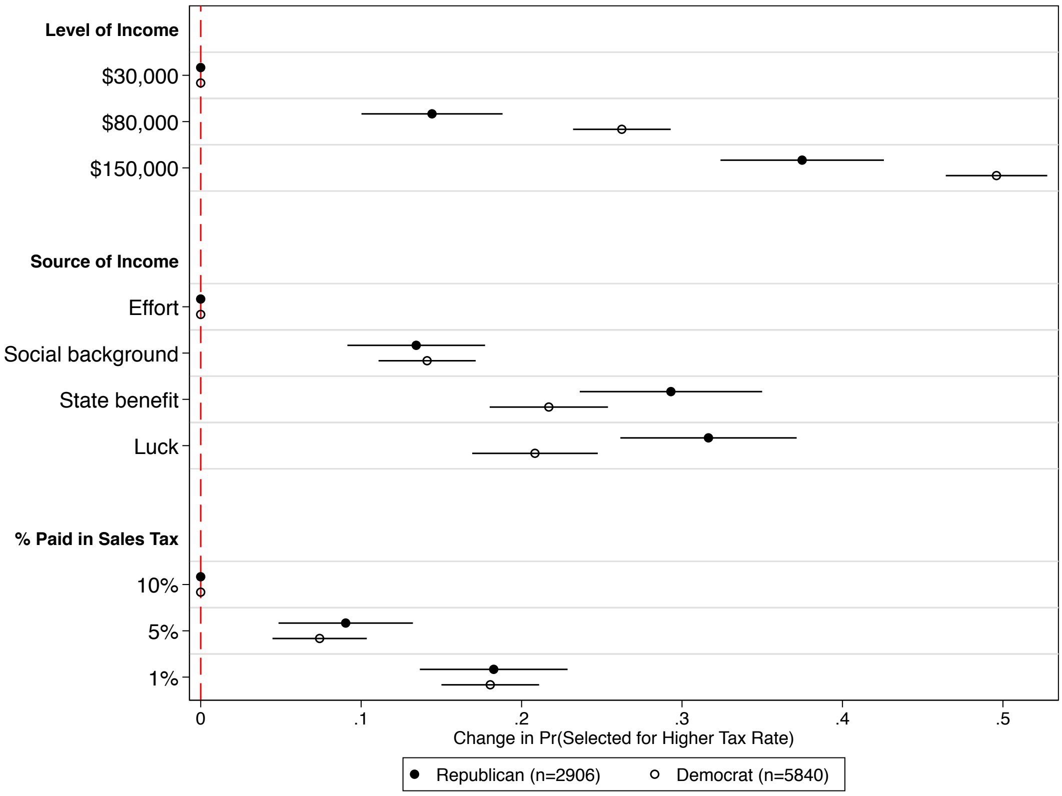
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for four different groups of respondents: those with annual incomes of $125,000 or above (very high income), between $80,000 and $124,999 (high income), between $30,000 and $79,999 (medium income), and under $30,000 (low income). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 82: Effect of Profile Attributes by Margins of Respondent Income



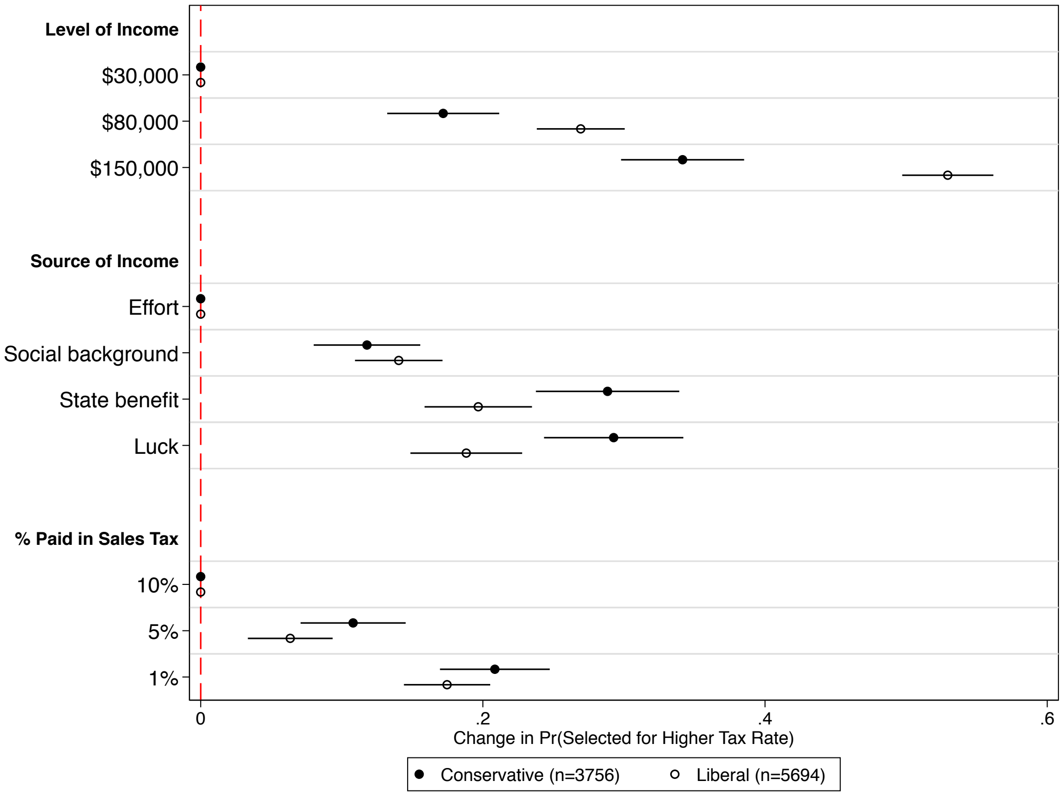
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of respondents: those with annual incomes between $20,000 and $39,999 (around $30,000), between $50,000 and $99,999 (around $80,000), and between $125,000 and $199,999 (around $150,000). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 83: Effect of Profile Attributes by Respondent Party Identification



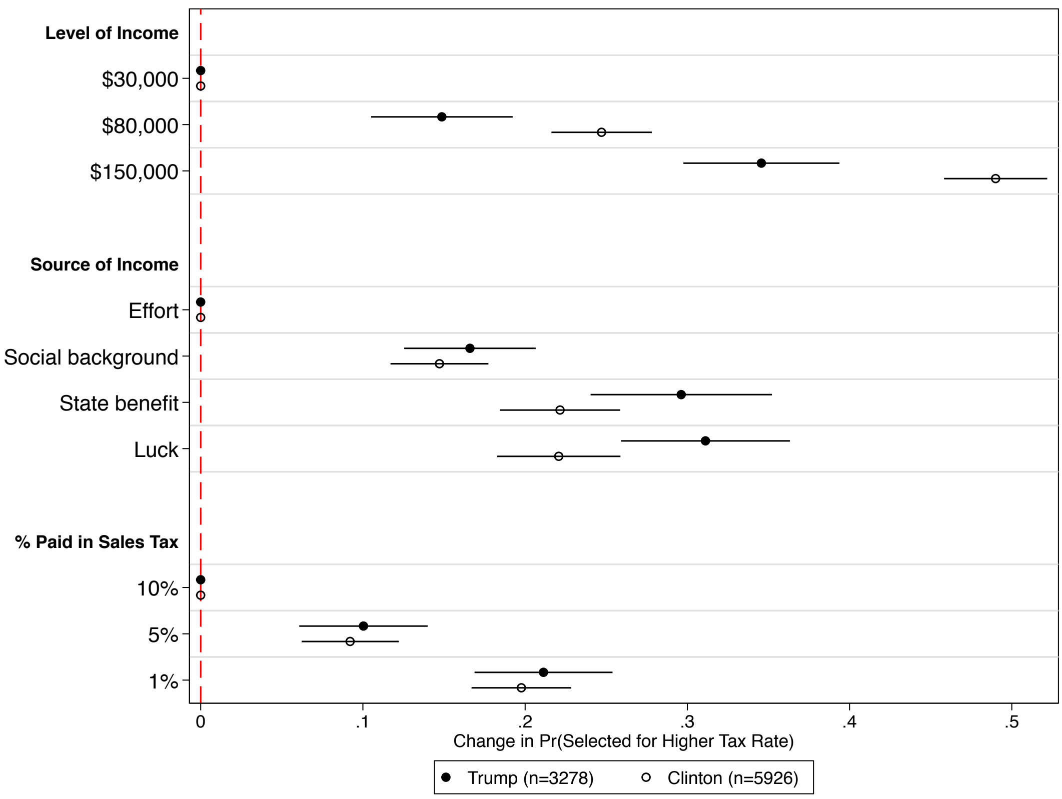
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: those who identify as Republicans, and those who identify as Democrats. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 84: Effect of Profile Attributes by Respondent Ideology



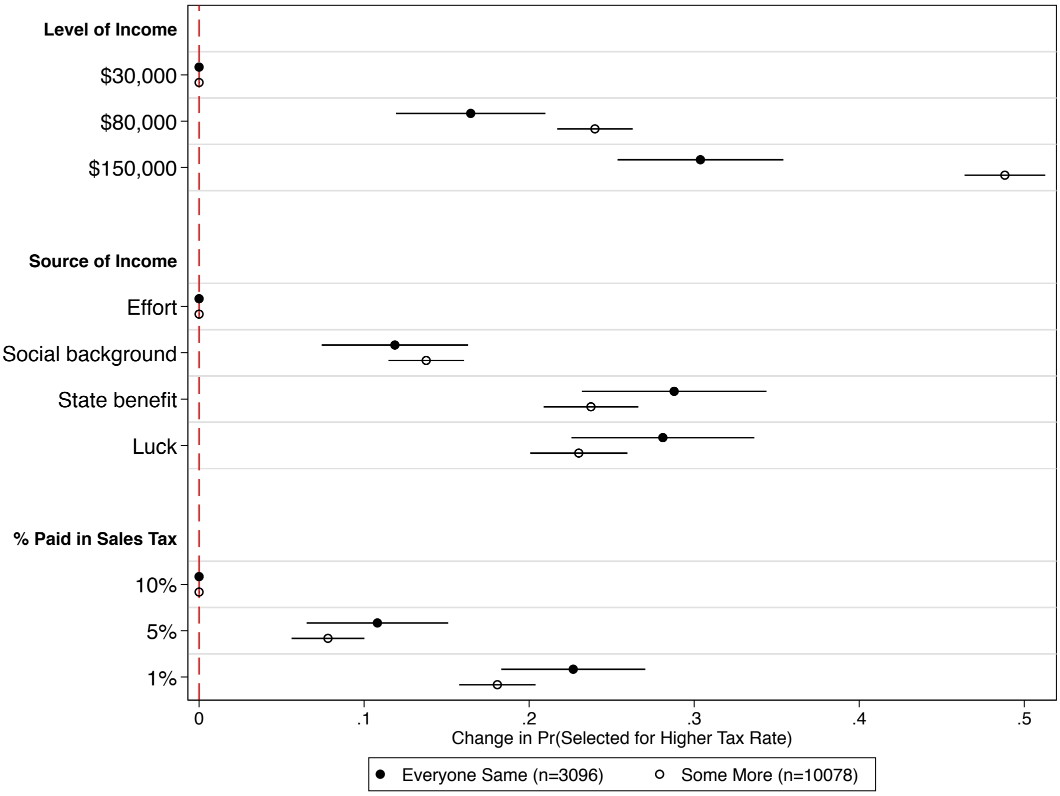
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: conservatives and liberals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 85: Effect of Profile Attributes by Respondent 2016 Vote Choice



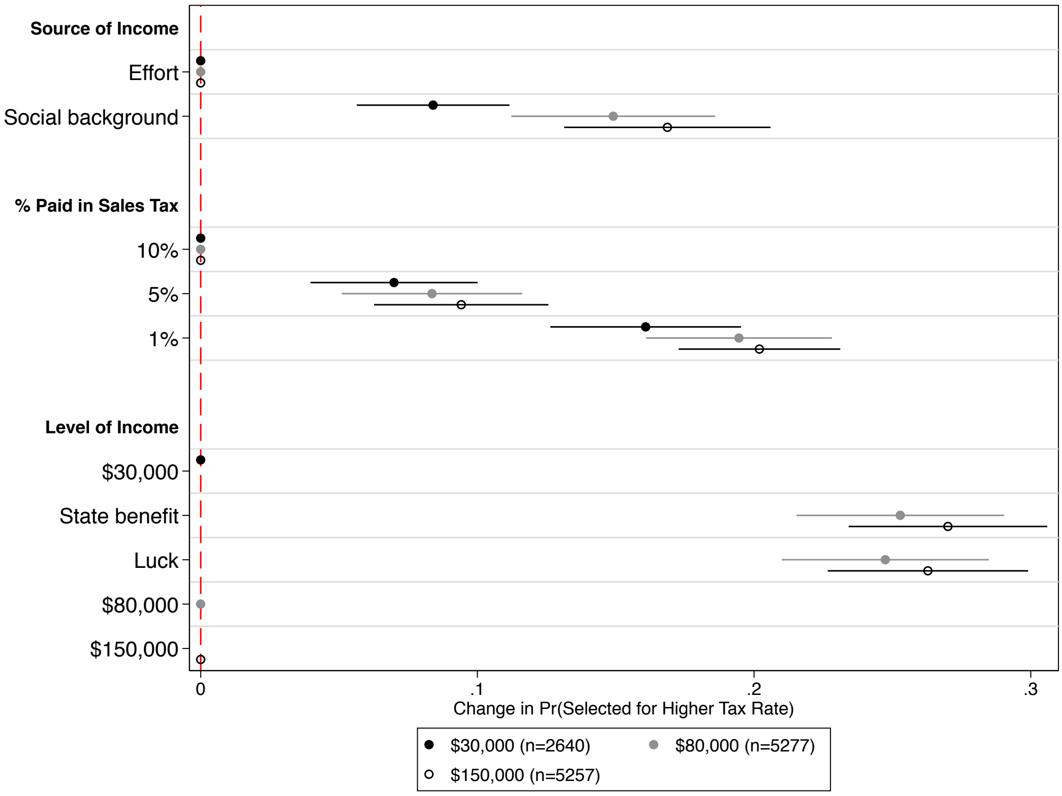
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two groups of respondents: those who voted for Trump and those who voted for Clinton in the 2016 presidential election. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 86: Effect of Profile Attributes by Respondent Adherence to Equal Treatment



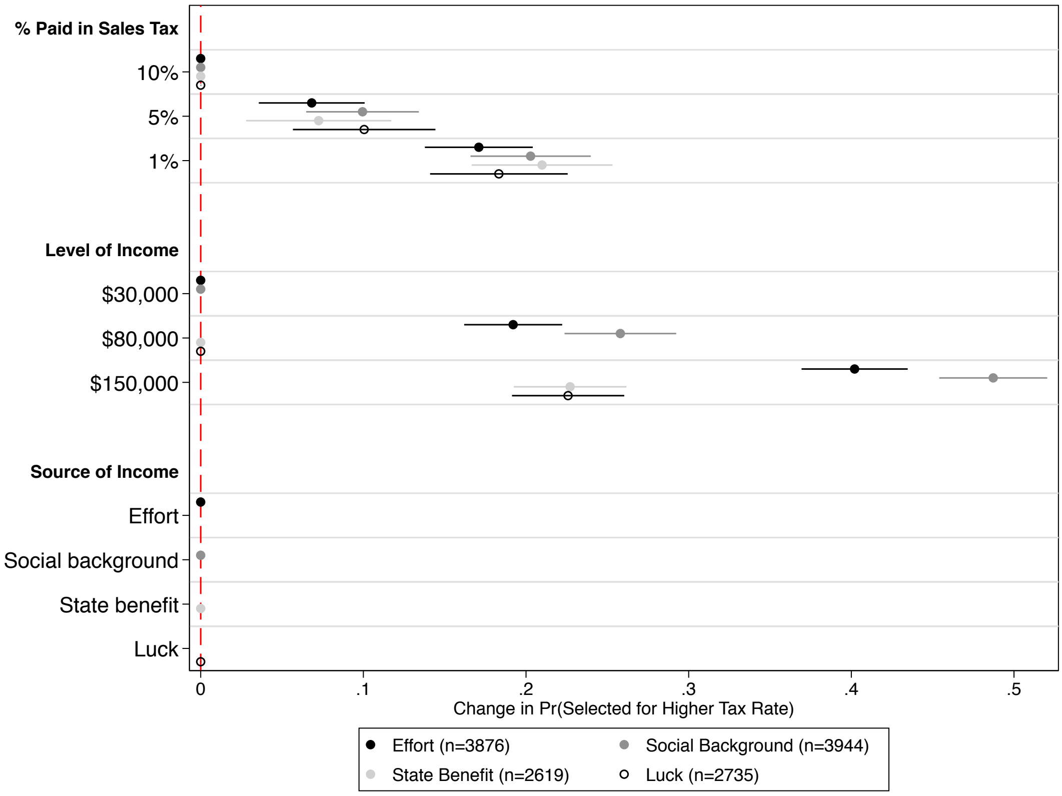
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for two different groups of respondents: those who think everyone should pay the same share of their income in taxes, and those who think some people should pay more than others. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 87: Effect of Profile Attributes by Level of Income in Profile



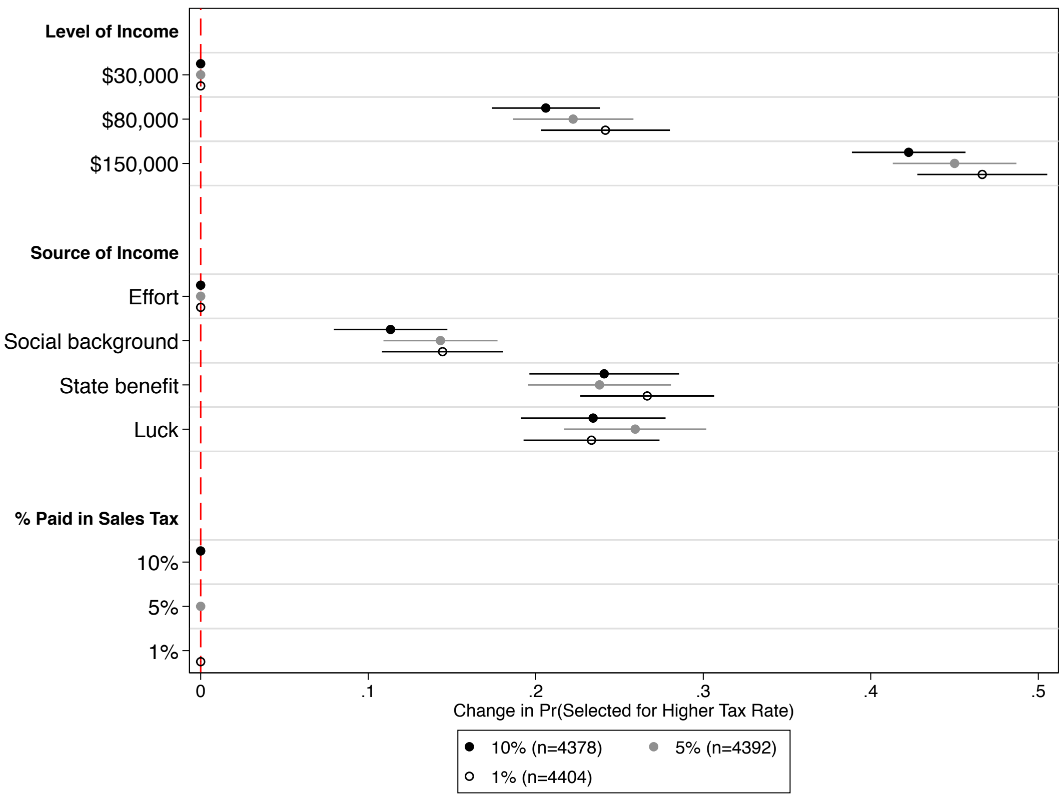
Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of profiles: those with income level $30,000, those with income level $80,000 and those with income level $150,000. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 88: Effect of Profile Attributes by Source of Income in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for four different groups of profiles: those with source of income "Started own small business" (effort), those with source of income "Got a job through family connections" (social background), those with source of income "Owns business that was bailed out by the government" (state benefit), and those with source of income "Receives annuity from lottery prize" (luck). The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure 89: Effect of Profile Attributes by Share of Income Paid in Sales Tax in Profile



Note: This plot shows estimates of the effects of the randomly assigned individual attributes on the probability of being selected to receive the higher tax rate. Estimates are based on the benchmark OLS model with robust standard errors clustered by respondent excluding pairs that included an atypical profile, estimated for three different groups of profiles: those with percentage of income paid in sales tax of 1, 5 and 10%. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

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