Perceptions of Intergenerational Mobility and Demand for Redistribution in Austria

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September 12, 2019

Abstract

This article studies intergenerational mobility perceptions in Austria. The following research questions - do they affect policy preferences and can exogeneously providing information change these perceptions and in turn the demand for redistribution? - are answered using an online survey conducted in Austria. First, I find evidence for a significant effect of mobility perceptions on the support for a wealth, an inheritance and a property tax. Quintile persistence perceptions, however, do not seem to be relevant for the forming of political preferences. Second, using a randomized information treatment, I show that these perceptions can be changed exogenously. Especially the effect on perceptions of income quintile persistence, i.e., rich children staying rich and vice versa for poor children, proves strong and robust. However, the demand for redistribution changes disproportionally little in turn. Only the support for the wealth tax differs significantly between the control and the treatment group.

1 Introduction

Growing inequality in the developed world poses an increasing number of threats to social peace and fosters conflict. At the same time, intergenerational mobility does not increase in the same way, but instead often decreases, which reinforces inequality and brings forward stronger segregation of society. Additionally, national tax systems are not adjusted to counter this development, and even the demand for redistribution in public opinion seems to be low (see Lübker, 2006; Sabirianova Peter, Buttrick, and Duncan, 2010). In this context, economists have argued that individuals do not build their policy preferences based on actual outcomes, but on their perceptions of it, which have shown to be systematically wrong (see Engelhardt and Wagener, 2014; Gimpelson and Treisman, 2018; Hauser and Norton, 2017). Further, there is evidence that these perceptions can be changed exogeneously by providing information (see Alesina, Stantcheva, et al., 2018; Cruces, Perez-Truglia, and Tetaz, 2013; Kuziemko et al., 2015). However, little research has been done on how people form these perceptions of economic reality, even though such research would be of high interest for democratic voting considerations.

In light of the following specifics of Austria, these issues are especially relevant there. The tax system is progressive for income, but not so for wealth and capital. The capital gains tax and the corporate tax are flat taxes, while wealth and inheritances are not taxed at all (see Altzinger, Humer, and Moser, 2017). The structure of the tax system, among other mechanisms, reinforces the strong concentration of wealth among a small group of elites in Austria. Further, in comparison to other European countries, the link between the father's and the son's income or education is strong (see Schnetzer and Altzinger, 2013). The OECD (2018) classifies it in the small group of countries, where not only income inequality, but also intergenerational mobility is low. Finally, among other countries in Europe, Austria recently had a conservative populist government, which did not tackle, but probably reinforced these inequality issues.

With this in mind, the following work tries to answer two research questions. Do perceptions of intergenerational mobility affect the demand for redistribution in Austria? Do both of these variables react to new information about intergenerational mobility?

2 Inequality and intergenerational Mobility Perceptions

Following the common theoretic economic model of Meltzer and Richard (1981), the fact that income and wealth inequality have risen sharply in developed countries in the last decades should have led to a higher demand for redistribution policies through the mechanism of the median voter theorem. This theorem states that in a majority rule voting system the preferred outcome of the median voter will succeed. Thus, if the distance between the mean and the median income in a national economy rises, the voting system will lead to more redistribution because the median voter would benefit from it (see Meltzer and Richard, 1981). However, in most developed countries, redistributive policies have been reduced or at least not been extended in the last decades (see Sabirianova Peter, Buttrick, and Duncan, 2010).

This inconsistency of the data with economic theory can be explained in various ways. Public opinion could not be directly transformed into policy outcomes, depending on the institutional system of the countries. The voter turnout among poor citizens could be low, elites could have a strong influence on governmental bodies, politicians may not fulfill their promises made in their campaign, etc. (see Finseraas, 2009; Kerr, 2014). Nevertheless, there is a constantly growing strand of literature that suggests that even the demand for redistributive policies among the population is lower than would be predicted by the model of Meltzer and Richard (1981) (see Lübker, 2006). Alesina and Giuliano (2011) argue that the demand for redistribution does not only depend on the level of inequality in a country, but also factors such as race, religion, cultural norms, family structure, and fairness perceptions. Some economists focused especially on this last factor and argued that people do not care so much about equality of outcome but more about equality of opportunities and fairness. Thus, if societies have unequally distributed wealth and income, but intergenerational mobility is sufficiently high, the demand for redistribution will be low. (see Alesina and La Ferrara, 2005; Bjørnskov et al., 2013; Piketty, 1995; Starmans, Sheskin, and Bloom, 2017) However, there is empirical evidence that intergenerational mobility has not risen as sharply as inequality (see Chetty et al., 2017; Hilger, 2015). Further, according to OECD (2018), there is no country in the OECD where income inequality and intergenerational mobility are both high. Finally, individual prospects of upward mobility do mitigate the support for redistributive policies, even though, these would be in the interest of the individual. Thus, people oppose redistributive policies because they expect to improve their position in society. This so-called "Prospects of upward mobility hypothesis" is widely stated in the literature and empirically contested (see Alesina and Giuliano, 2011; Benabou and Ok, 2001; George, 2017).

Additionally to these explanations, an increasing number of economists have focused on perceptions of inequality and intergenerational mobility and not on actual outcomes and have found convincing evidence of their importance for the demand for redistribution (see Alesina, Stantcheva, et al., 2018; Engelhardt and Wagener, 2014; Gimpelson and Treisman, 2018; Hauser and Norton, 2017; Niehues, 2014). The difference here is that people's perceptions of the actual state of society are vastly wrong. Most groups in society tend to underestimate inequality and overestimate upward intergenerational mobility. Furthermore, poorer social classes usually overestimate their position in society, while the richer underestimate it. The biases of people depend on characteristics such as their political ideology, their position in society, cultural norms and reference groups. (see Alesina, Stantcheva, et al., 2018; Chambers, Swan, and Heesacker, 2015; Davidai and Gilovich, 2015; Gimpelson and Treisman, 2018; Hauser and Norton, 2017; Norton and Ariely, 2011) Thus, those who overestimate their own position will demand limited redistribution, even though they would likely benefit from it, and vice versa. The estimates about average earnings in the economy will be positively correlated with own income and inequality, in general, will be underestimated, resulting in downward biased demand for redistribution. (see Cansunar, 2016; Cruces, Perez-Truglia, and Tetaz, 2013; Knell and Stix, 2016; Windsteiger, 2017) Finally, Flynn, Nyhan, and Reifler (2017) emphasize the political relevance of systematic misperceptions of reality, especially in democratic states, where they influence the public and political debate and in turn, voting outcomes. If these misperceptions are not random but systematic, the argument for a democratic system based on the aggregation of individual-level opinions to receive a better estimate of public opinion is invalid. (see Flynn, Nyhan, and Reifler, 2017)

Consequently, a highly politically relevant question is, whether it is possible to correct these misperceptions externally and, subsequently, whether the demand for redistributive policies reacts to that. This argument has already been tested using experimental research designs and researchers examined further how these changed perceptions of inequality influence the demand for redistribution (see Boudreau and MacKenzie, 2018; Cruces, Perez-Truglia, and Tetaz, 2013; Kuziemko et al., 2015; Zilinsky, 2014). In the field of misperceptions of intergenerational mobility less work has been done (see Alesina, Stantcheva, et al., 2018; George, 2017). Especially the work of Alesina, Stantcheva, et al. (2018) has been very influential and path-breaking in this context. Most of the results confirm that perceptions of inequality or intergenerational mobility react to new information, however, that this changes political preferences disproportionally little. Arguments to explain these findings are a lack of trust in the government or ideological views of society. (see Alesina, Stantcheva, et al., 2018; George, 2017; Kuziemko et al., 2015; Zilinsky, 2014) Kuziemko et al. (2015) further highlight that the effect of the correction of misperceptions of inequality on policy preferences can be underestimated if poorer people systematically overestimate their position in society.

3 Methodology

3.1 Hypotheses and methods

Hypothesis 1: Perceptions of intergenerational mobility affect the demand for redistribution.
According to Alesina, Stantcheva, et al. (2018) and Engelhardt and Wagener (2014) perceptions of intergenerational mobility play an important role in shaping the political preferences of individuals. By using the various variables concerning support for redistribution policies and the mobility perception variables in the dataset, I can construct the following model:

$$E[support = 1|mobility\,perceptions, \mathbf{X}_{i,j}] = G(\beta_0 + \beta_1 * log(mobility\,perception_i) + \beta_j * \mathbf{X}_{i,j}) \quad (1)$$

$$E[tax\ rate|mobility\,perceptions, \mathbf{X}_{i,j}] = \beta_0 + \beta_1 * log(mobility\,perception_i) + \beta_j * \mathbf{X}_{i,j} \quad (2)$$

$\mathbf{X}_{i,j}$ represents several control variables including age, gender, education, being in the highest of three income groups, political ideology, urbanisation, and the wave of the survey. The choice of control variables follows Alesina, Stantcheva, et al. (2018). Wave fixed effects are included to control for any systematic differences between the two waves, which could emerge because of slight differences in the placement of some questions and the general pool of survey questions between the waves. The treatment is additionally included as a control variable in both equations to control for the effect of the treatment. The effects of the mobility perception variables are estimated in separate regressions, due to the high correlation between them. The mobility perceptions variables can take values between 0 and 100. The variables were logarithmized to reduce the effect of outliers and be able to compare the effects between the four mobility variables, which will be described more closely below and which are of very different magnitudes. Support indicates whether an individual supports a specific tax policy or not, and takes the value 0 or 1. The different taxes, which are inquired in the survey, will be described in section 3.2. The model used to estimate the effect of intergenerational mobility perceptions on the demand for redistribution, specified in equation 1, is estimated as a logistic regression to account for the binary nature of the dependent variables. Thus, in equation 1, the G() specifies the logistic function. Equation 2 specifies the estimated model for the continous dependent policy variable and is estimated as an OLS. The variables are described below in more detail. This hypothesis lays the ground for hypothesis 2.

Hypothesis 2: Pessimistic information about the extent of intergenerational mobility causally affects intergenerational mobility perceptions and the demand for redistribution.
Following the work of Alesina, Stantcheva, et al. (2018); George (2017); Kuziemko et al. (2015) and Zilinsky (2014), I argue that perceptions of economic reality are subject to change when people are confronted with new information. This effect can be causally investigated using a randomized information treatment in the dataset under the assumption that the treatment was assigned randomly. The hypotheses are thus that neither the mobility perceptions nor the demand for redistribution differ significantly between the treatment and the control group.

I will test hypothesis 2, by estimating treatment effects on mobility perceptions and demand for redistribution, as it is done in the literature (see Alesina, Stantcheva, et al., 2018; Boudreau and MacKenzie, 2018; Kuziemko et al., 2015; Zilinsky, 2014). Especially the methodological framework of Alesina, Stantcheva, et al. (2018) is relevant in this context, due to the strong similarities regarding the mobility perception variables and the information treatment. They investigate the effects of a randomized information treatment on perceptions of upward mobility and preferences of redistribution in the U.S. and four other developed countries. Furthermore, the authors compare the perceptions of intergenerational mobility to data about the actual amount of intergenerational mobility and indicate heterogeneous treatment effects for different political ideologies. The following equations illustrate my regression models, used to test hypothesis 2:

$$E[log(mobility\,perceptions)|treatment, \mathbf{X}_{i,j}] = \beta_0 + \beta_1 * treatment_i + \beta_j * \mathbf{X}_{i,j} \tag{3}$$

$$E[support = 1|treatment, \mathbf{X}_{i,j}] = G(\beta_0 + \beta_1 * treatment_i + \beta_j * \mathbf{X}_{i,j}) \tag{4}$$

$$E[tax\ rate|treatment, \mathbf{X}_{i,j}] = \beta_0 + \beta_1 * treatment_i + \beta_j * \mathbf{X}_{i,j} \tag{5}$$

$\mathbf{X}_{i,j}$ refers to the same variables as described for equations 1 and 2. Treatment is a dummy taking the value of 1 if the respondent has seen the treatment. The mobility perception variables were again logarithmized. Equation 4 and 5 are analogous to equations 1 and 2, except that the treatment dummy replaces the mobility perception variables. Equation 3 and 5 are estimated by OLS, where β_1 represents the treatment effect under the assumption that the effect is linear. This effect can be causally interpreted if the treatment group is a valid counterfactual for the control group, and the treatment has been assigned randomly, which is tested in the appendix. [1] Equation 4 is estimated anaologously to equation 1 as a logistic regression model for the binary dependent variables.

Finally, some robustness checks are conducted, which can be seen in the appendix.

3.2 The Survey

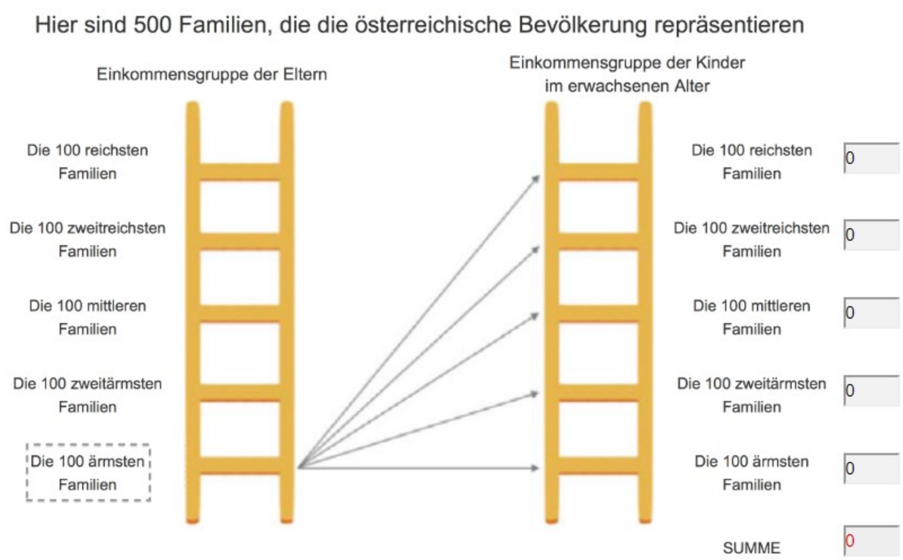
I work with data from two online surveys, conducted by "YouGov" which took place in Austria in 2018 and 2019. I will merge these two surveys to reach a bigger sample which includes 4200 people and is representative for the Austrian population in terms of age, gender, and education. After reducing the sample using quality checks included in the survey, I get 2133 observations. If not explicitly stated otherwise, all following calculations will be done using this dataset. The exact process of sample reduction is described in the appendix. Although the survey institute delivered ready-made frequency weights for the dataset, I recalculated weights along the lines of gender, age and education to suit my sample better. A through description of this reweighting process can be

[1] If the treatment fulfills these assumptions, the control variables would not be needed. They are however included in the regressions because differences between both groups could still arise and have to be controlled for. Nevertheless, the models without any control variables lead to the same treatment effects, which indicates that the treatment is randomised.

found in the appendix. In the following, I will describe the construction of the variables I am going to use.

- *Intergenerational Mobility Perceptions:* The intergenerational mobility perceptions of respondents constitute the key variables in this paper. They are examined analogously to Alesina, Stantcheva, et al. (2018), while additionally enquiring downward mobility perceptions. Figure 1 shows the corresponding question for upward mobility in the survey. Respondents were asked to assign 100 children from the poorest income quintile on the right ladder, representing their income quintile when they are grown up. The same framework is used for 100 children of the richest families.[2] Upward mobility is in the following defined as those children from the bottom quintile expected to reach quintile 5 (Q1Q5 in the following) and downward mobility vice versa (Q5Q1). Additionally, to measure persistence, the number of children staying in the bottom (Q1Q1) or the top quintile (Q5Q5) will be used for analysis.

  Figure 1: Question about intergenerational mobility perceptions

  As a robustness check, the calculations are repeated after changing the definition of up- and downward mobility. Upward mobility is then defined as all children from the bottom quintile reaching the two richest quintiles and downward mobility vice versa.

- *Demand for redistribution:* The dataset offers a variety of policy opinion variables. The approval to taxes addressing the top of the distribution, such as inheritance tax, wealth tax, property tax, and capital gains tax is queried. Response categories for the first three are "support", "support with amount of exemption", and "oppose". However, for calculations, the categories "support" and "support with exemption" are combined to a single category, due to the small number of observations choosing "support". For the capital gains tax, respondents were asked to state their preferred tax rate, while informing them that the

[2] Those, whose answers did not sum up to 100 were omitted from the dataset by the survey institute and are not included in the 4200 total observations.

current rate is 25%.[3]

- *Information Treatment:* The randomized information treatment experiment consisted of pessimistic, but general information about intergenerational mobility in Austria and was shown to 50% of the survey participants. In the first wave, due to a mistake of the survey institute, the treatment was only presented after the question about the inheritance tax. Thus, for the calculations for the inheritance tax, the treatment group is only around 25% of the population. This makes it harder to identify treatment effects for this tax and has to be kept in mind when interpreting the treatment results. A detailed discussion of the treatment can be found in the appendix.

The remaining important variables are described more thoroughly in the corresponding section in the appendix.

4 General Results

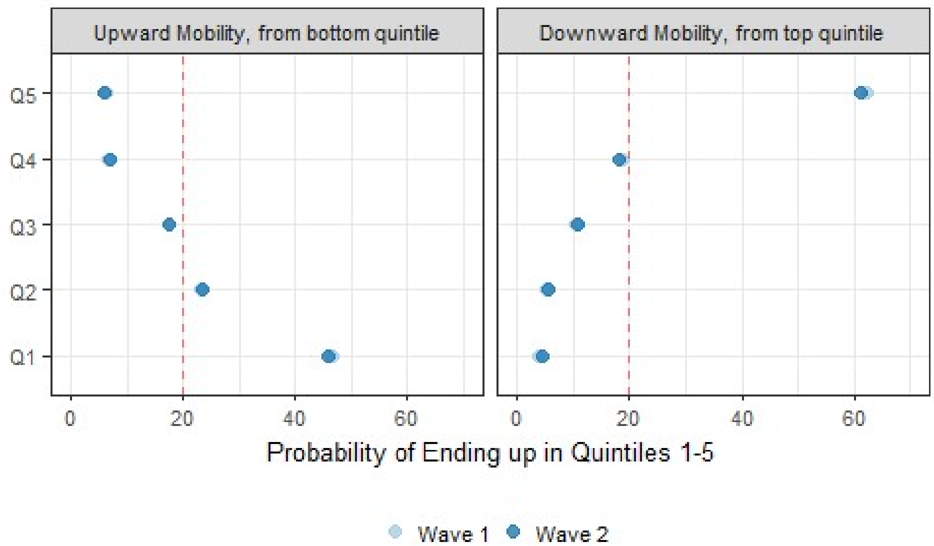
4.1 Descriptive Analysis

In general, respondents believe more in upward than downward mobility, which is in line with previous findings. On average people estimate about 10% of kids from the bottom quintile to end up in the top, while only 7% of those at the top are expected to end up in the bottom quintile. In consonance with that, rich people are estimated to stay in their quintile on average 56% of the time, while only 41% of poor people are assumed to remain at the bottom. One can see this asymmetry well in figure 2. Further, the graph indicates that there are no differences in answers on average between the two survey waves. However, a wave dummy is included as a control variable in all models to control for any differences that could result from this. Additionally, the dispersion measures for the mobility perception variables for the restrictive dataset are shown in table 9 in the appendix. The persistence variables are higher than the mobility variables and show more variance as well. The broader mobility perception variables are higher and vary more than the original mobility perceptions. A comparison of the mobility perception variables between the datasets can be found in the appendix.
The perceptions of intergenerational mobility vary across different subgroups of society, as can be seen in table 8 in the appendix. The most significant difference can be seen for the highest achieved education level. The higher the education, the lower are upward as well as downward mobility perceptions. This is relatively more pronounced for downward mobility, thus the estimate of kids from the richest quintile ending up in the poorest. In line with that, people in the upper class have much lower expectations of intergenerational mobility than those in the lower or middle class. This is in agreement with the literature about "system justification" of the lower classes (see Jost, Banaji, and Nosek, 2004). However, the difference is less pronounced than for different education levels. Further, people who see themselves as progressive believe much less in upward as well as downward mobility than middle or conservative groups. The difference is the smallest

[3] The special situation in Austria, where neither an inheritance tax nor a wealth tax has been in place for a relatively long period, is beneficial for a survey analysis because the respondents are not primed in what the exact parameters such as tax rate or amount of exemption, etc. are.

for moving from the first to the top quintile and the biggest for staying in the top as well as the bottom quintile.

Figure 2: Mobility perceptions for both waves



Interpretation example: Respondents of wave 1 and 2 state, on average, that around 50 out of 100 poor children stay in the bottom quintile.

Subsequently, the survey participants were asked if they support an inheritance tax, a wealth tax, and a property tax. While only 34% of the respondents support an inheritance tax, 50% and 62% support a wealth and a property tax, respectively, as is shown in table 1.

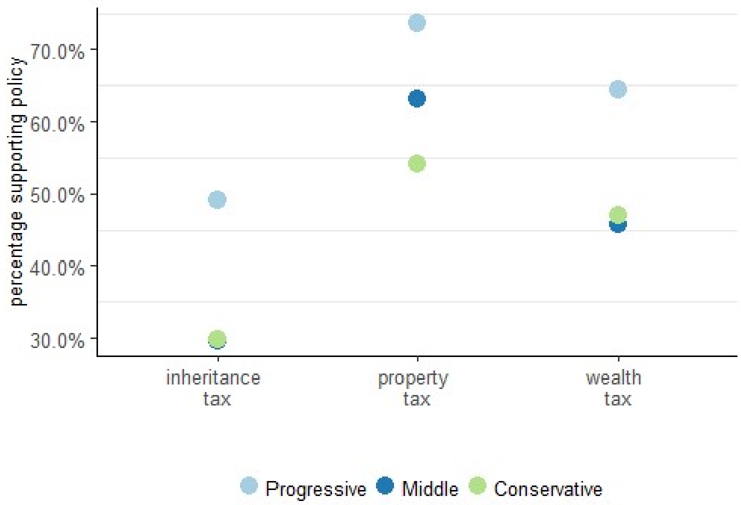
Table 1: Demand for redistribution

	Inheritance		Wealth		Property	
	support	oppose	support	oppose	support	oppose
	(1)	(2)	(3)	(4)	(5)	(6)
Total	34.32	65.68	50.18	49.82	62.62	37.38

The table shows the weighted average share of respondents supporting and opposing the taxes.

These preferences differ between different subgroups of society. In general, men are more in favour of these taxes than women, which is slightly surprising, as women tend to favour redistribution more than men, according to previous research results (see Alesina and Giuliano, 2011). The support for all three taxes increases with age and the highest education completed. Although overall support is bigger for higher classes, this is almost entirely attributable to increased support for taxes with an exemption. People who consider themselves progressive have significantly higher rates of support for all tax categories. Figure 3, which illustrates these differences, shows that especially support for inheritance tax nearly doubles when comparing conservative to progressive people. Finally, mobility perceptions play a decisive role, as well. People supporting these taxes have lower upward as well as downward mobility perceptions than those who do not.

Figure 3: Demand for redistribution by economic ideology



Interpretation example: Around 65% of respondents, who state that they are politically progressive, support the wealth tax, while only around 45% of those, who state they are in the middle or conservative, do.

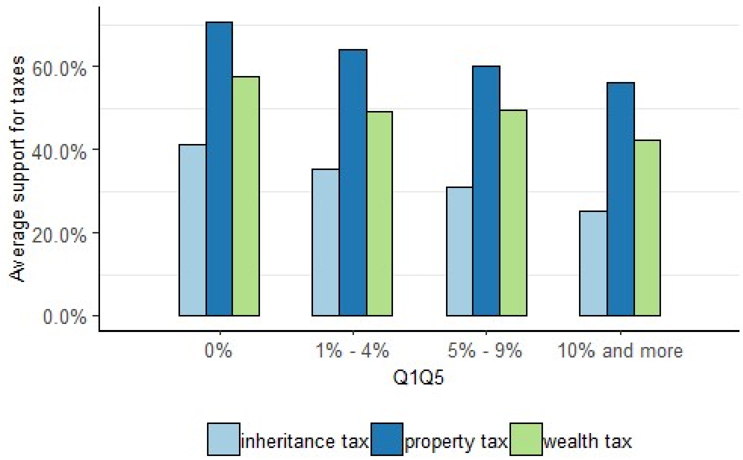
When looking at the answers for the capital gains tax, the differences are not that pronounced, because the question was different. People were explicitly asked which rate they would prefer for the capital gains tax. The overall average answer was around 18%, which is below the current rate in Austria. Again, men, higher educated people, and those who see themselves as progressive favor higher rates. However, these differences are rather small. Other variables do not show clear lines of difference.

4.2 Effects of Perceptions on Policy Preferences

For figure 4 and figures 11 to 13 in the appendix the mobility perception variables were split in categories, according to their distribution, to receive categories with roughly the same amount of respondents. These figures show that the demand for redistribution is correlated with the answers to the mobility perception variables. For the perceptions of upward mobility a clear trend to less support for redistributional policies can be seen as the perceived upward mobility increases. Analogous conclusions can be made for the other mobility perception variables.

However, the effects of the persistence perception variables seem to be negligible, when analysing the relationship using the regression model, explained in section 3 in equation 1, as can be seen in table 2. The effects of Q1Q5 and Q5Q1 on the support for the three taxes are sizable. For example, if the perception of downward mobility increases by 10% the support for the wealth tax decreases by 30% points. Thus, the beliefs about downward mobility seem to be especially relevant for the support for taxes, which affect mostly the top of the income distribution. Finally, there seems to be no effect of perceptions of intergenerational mobility on the preferred capital gains tax rate. To address reverse causality or omitted variable bias issues the endogeneity of the mobility variables in the following models was tested and rejected.

Figure 4: Demand for redistribution by upward mobility perceptions



Interpretation example: Around 65% of respondents, who state that they are politically progressive, support the wealth tax, while only around 45% of those, who state they are in the middle or conservative, do.

Table 2: Effects of mobility perceptions on policy preferences

	Dependent variable:			
	wealth tax	inheritance tax	property tax	log(capital gains tax)
	(1)	(2)	(3)	(4)
log(Q1Q5)	-0.018^{***}	-0.020^{***}	-0.016^{***}	-0.037
	(0.006)	(0.006)	(0.004)	(0.041)
log(Q1Q1)	0.001	0.002^{***}	0.001^{*}	0.033
	(0.001)	(0.001)	(0.001)	(0.055)
log(Q5Q1)	-0.030^{***}	-0.022^{***}	-0.022^{***}	-0.059
	(0.007)	(0.008)	(0.006)	(0.048)
log(Q5Q5)	0.002^{**}	0.001^{**}	0.001^{**}	0.022
	(0.001)	(0.000)	(0.000)	(0.055)
Observations	1,836	1,937	2,072	1,781

Note: *p<0.1; **p<0.05; ***p<0.01

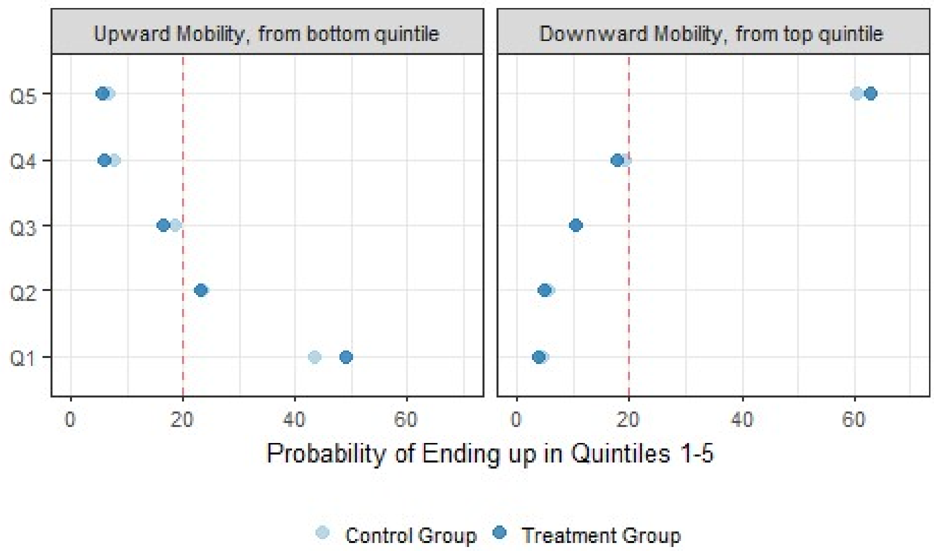
All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology, urbanisation and the wave. The first three regressions are weighted logistic regressions and the last one a normal linear regression. Coefficients in the first three columns are average marginal effects. White's heteroskedasticity-robust standard errors (only for column 4) are reported in parentheses. The estimates for the different mobility perception variables result from separate regression models due to the high correlation among them. The estimates in joint regression models are only slightly smaller in size, but have no statistical power. The differences in observations per model and to the whole restrictive dataset result from item non-response of the dependent variables and the independent variable urbanisation.

5 Treatment Results

5.1 Treatment Effects on Perceptions

Table 3 and figure 5 show the treatment effects on mobility perceptions.

Figure 5: Visual treatment effects on mobility perceptions



Interpretation example: On average respondents in the control group think that around 42 out of 100 poor children will stay in the bottom quintile, which is about 8 less than those in the treatment group.

Those who were treated believe significantly less that children from the bottom quintile will reach the top. More specifically, being in the treatment group decreases the estimated share of poor people becoming rich by nearly 20%. The effect on the perceptions that people stay at the top or the bottom of the income distribution is slightly smaller but still sizable. The treatment increased the share of children thought of staying in the bottom quintile, by 13%, and by 7% for the top quintile respectively. Finally, there is no significant treatment effect on the share of rich children ending up poor. This can partly be explained by the low variance in this variable, as people agree very much that this share is low. These results support hypothesis 2, regarding the effect of the treatment on mobility perceptions. It can thus be rejected that mobility perceptions do not differ between the treatment and the control group.

Table 3: Treatment effects on mobility perceptions

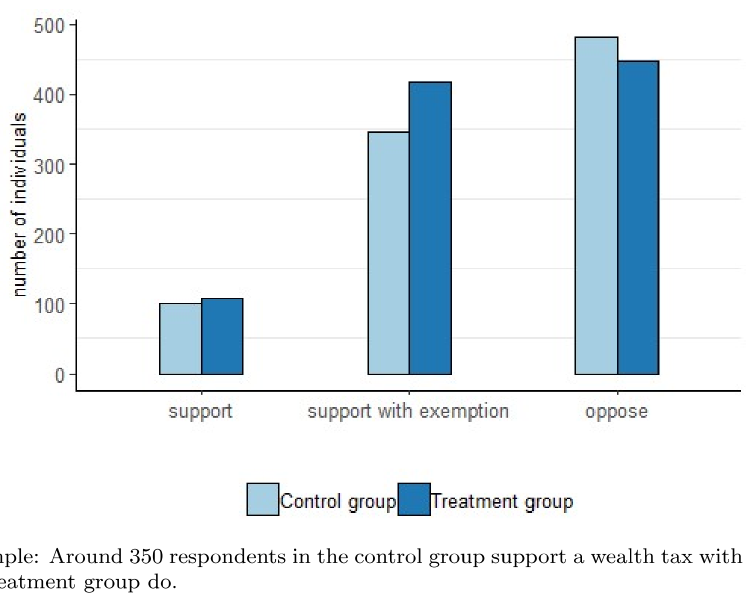
	Dependent variable:			
	log(Q1Q5)	log(Q1Q1)	log(Q5Q1)	log(Q5Q5)
	(1)	(2)	(3)	(4)
treatment	-0.180^{**}	0.117^{***}	-0.026	0.077^{***}
	(0.082)	(0.034)	(0.068)	(0.022)
Observations	2,072	2,072	2,072	2,072
Note:				*p<0.1; **p<0.05; ***p<0.01

All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology, and the wave. White's heteroskedasticity-robust standard errors are reported in parentheses. The differences in observations between the whole restrictive dataset and the models result from item non-response of the independent variable urbanisation.

5.2 Treatment Effects on Policy Preferences

In the following, the effect of the treatment on policy preferences will be analysed. Figure 6 shows that the increased support for a wealth tax through the treatment is mostly resulting from more support for the wealth tax with an exemption amount. Additionally, figure 7 shows that those in the treatment group more often choose 25% as the preferred rate for a capital gains tax and less often 0%. Thus, they tend to support the current regulation in Austria more.

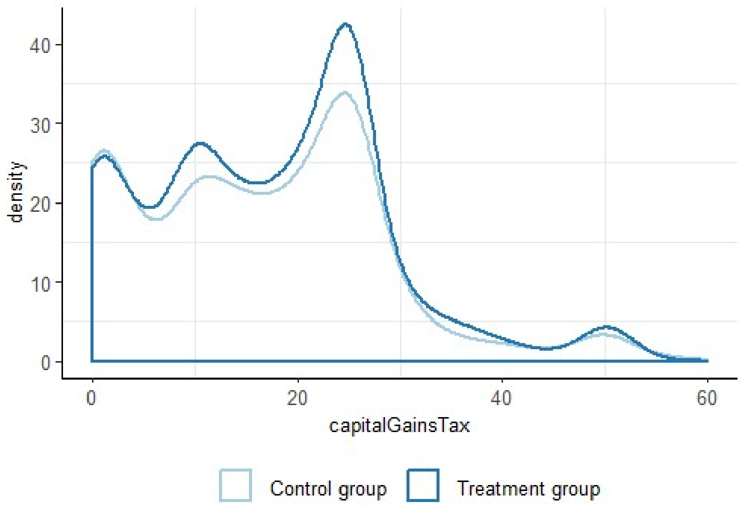
Figure 6: Visual treatment effects on wealth tax support



Interpretation example: Around 350 respondents in the control group support a wealth tax with exemption, whereas about 400 of the treatment group do.

As can be seen in table 4, the treatment has a significant effect on support for wealth tax only. The treatment increases support for the wealth tax by 6 % points. Despite the lack of significance, the treatment increases the preferred rate of the capital gains tax by 13 %. The treatment does not show a significant effect on the property or the inheritance tax. The missing effect on the inheritance tax can, however, result from the mistake of the survey institute, through which fewer

Figure 7: Visual treatment effects on the preferred capital gains tax rate



Interpretation example: A bigger share of respondents in the treatment group stated 25% as preferred rate for the capital gains tax than did in the control group.

respondents saw the treatment before the question of the inheritance tax. The effects on policy preferences are significantly smaller than the treatment effects on mobility perceptions, seen in table 3. This is in line with the literature, where policy opinions are mostly less elastic to information than the variable that is directly treated, see section 2. Further, considering the results of table 2, the lack of a treatment effect on the policy variables can possibly be explained by the missing treatment effect on downward mobility perception, which shows the biggest effects on the policy variables. Thus, I find evidence, which only partly supports hypothesis 2, concerning demand for redistribution. Support for wealth tax is significantly different between the control and the treatment group, but the other policy variables do not differ significantly.

Table 4: Treatment effects on policy preferences

	Dependent variable:			
	wealth tax	inheritance tax	property tax	log(capital gains tax)
	(1)	(2)	(3)	(4)
treatment	0.061**	0.000	−0.004	0.133
	(0.024)	(0.031)	(0.021)	(0.084)
Observations	1,836	1,937	2,072	1,781
Note:				*p<0.1; **p<0.05; ***p<0.01

All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology and the wave. The first three regressions are weighted logistic regressions and the last one a normal linear regression. Coefficients in the first three columns are average marginal effects. White's heteroskedasticity-robust standard errors (only for column 4) are reported in parentheses. The differences in observations per model and to the whole restricitive dataset result from item non-response of the dependent variables and the independent variable urbanisation.

6 Conclusion

In this paper, I analyse the effects of an information treatment on intergenerational mobility perceptions and the demand for redistribution in Austria and the relationship between these two key variables. Recollecting the hypotheses formulated in section 3 the results can be summarized as follows.

Hypothesis 1 cannot be rejected. There seems to be a sizeable effect of mobility perceptions on policy preferences, except for the preferred rate of the capital gains tax. The effect of upward mobility perceptions proves very robust in all datasets, while the effect of downward mobility is not robust for the inheritance tax and the wealth tax in the full sample. Perceptions of quintile persistence, however, do not show relevant effects on any of the policy variables. Further, there is clear evidence supporting *Hypothesis 2*. The information treatment has a sizable effect on perceptions of intergenerational mobility, ranging from 20% on Q1Q5 to 7% for Q5Q5. These effects did prove robust in several checks. The effect on demand for redistribution, however, is less strong. Only the effect on support for the wealth tax proves robust. This less than proportional effect on policy preferences is in line with the literature (see Alesina, Stantcheva, et al., 2018; Boudreau and MacKenzie, 2018; Cruces, Perez-Truglia, and Tetaz, 2013; George, 2017; Hauser and Norton, 2017; Hoy and Mager, 2018; Kuziemko et al., 2015; Zilinsky, 2014).

In general, there are several problems related to the dataset, which have as well to be considered, when interpreting the results. The dataset is only weighted along the lines of age, education, and gender, but I cannot account for a biased sample based on any other characteristics, most importantly income. Further, I cannot control for non-sampling errors such as unit non-response, measurement errors or coverage errors, which are especially an issue in surveys conducted based on online panels. Additionally, the high number of observations which are omitted through the quality checks could be an indication for low data quality and reinforces problems concerning representativity, due to the non-random exclusion of many observations. Thus, external validity of the results is questionable. However, internal validity is increased by the data checking procedure and the randomized treatment further ensures that the treatment effects can be interpreted causally.

Finally, my work indicates several interesting starting points, where further investigation could prove fruitful for the economics discipline. A more thorough understanding of what mechanisms shape (mis)perceptions of economic reality in the first place would be of great interest and also provide a better ground for research analysing their implications for policy opinions. Effects of personal experience or reference groups on perceptions are found in the literature (see Armona, Fuster, and Zafar, 2018; Knell and Stix, 2019; Cruces, Perez-Truglia, and Tetaz, 2013). Additionally, Flynn, Nyhan, and Reifler (2017) point out the role of political elites and the media discourse in the shaping of perceptions. In this context, it is as well important to ask, who has misperceptions and who doesn't and who profits by reinforcing these misperceptions. Furthermore, misperceptions pose a problem for democratic voting to the extent that they translate into aggregate voting outcomes. Therefore, it is of great political interest to analyse whether misperceptions follow a systematic or a random pattern. Eventually, misperceptions can only be identified as such, if data is available about the actual situation, which is not the case in Austria and many other European countries for intergenerational earnings mobility. Better access to these forms of data would most likely not only benefit the research community, but also the general public.

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Appendix

Figure 8: Treatment (1)

Figure 9: Treatment (2)

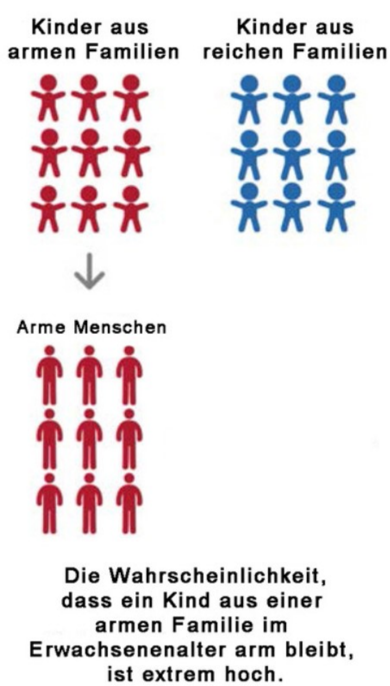


Figure 10: Treatment (3)

The Survey

Due to the merging of the two waves and the substantial reduction of the sample due to quality checks, my final sample differs significantly from the original two samples of the survey institute. I calculated post-stratification frequency weights, which are calibrated to match the marginals of specific characteristics of my sample to known marginals of the target population. They were computed using the raking method, an iterative process to account for marginals of more than one variable. I calculated the weights for the marginals of the variables gender, age, and education, where age and education are composed of three groups, respectively, which can be seen in tables 5 and 6. My target population are Austrian citizens over the age of 17. Thus, I can control for differences along the lines of these three variables between my sample and the target population. However, I cannot adjust for differences according to other variables or other problems related to survey data, such as non-sampling errors such as unit-non-response, coverage errors, or measurement errors. (see Groves et al., 2011)

- *Information Treatment:* The information shown was that "the probability that a child from a poor family stays poor in adulthood is extremely high" and that "only very few kids from poor families succeed in becoming rich when they are adults". The corresponding statements were shown for children of rich families as well. Additionally, the statements were supported by graphical illustrations, and it was emphasised that this information is resulting from research findings.[4] Anew, this is analogous to Alesina, Stantcheva, et al. (2018), who, however, only use information about poor children. It was designed to exogenously decrease the perceptions of up- and downward mobility of the treated respondents. The information presented is very general and open to subjective interpretations of respondents. Thus, respondents could interpret the treatment differently. This, however, has the benefit that the respondent's perceptions of intergenerational mobility are always either decreased or not affected, but not increased, independently of the prior perceptions of the individual. Further, Alesina, Stantcheva, et al. (2018) argue, not to use specific numbers in their treatment to reduce experimenter induced demand and avoid respondents just repeating the numbers they saw in

[4]The exact treatment about poor children is shown in figures 8 to 10 in the appendix. The information about rich children is presented in the exact same way.

the treatment and not grasp the meaning of it. Thus, the treatment effect can be interpreted as the effect of information, that should make individuals more pessimistic, but not as the effect of information, that corrects respondent's views.

- *Urbanisation:* Using the information about postal codes I will construct a variable, according to the Degree of Urbanisation (DEGURBA) classification 2012 of the European Commission (see Eurostat, 2012). The variable will have three levels, representing an urban, a semi-urban, and a thinly populated environment of the home address. I will use readily available tables of the Statistik Austria, connecting postal codes with the degree of urbanisation according to the definition of the European Commission (see Statistik Austria, 2018).
- *Age:* Age is split into three age groups, according to the groups for re-weighting the dataset. Respondents under 35 are in the youngest age group, those over 55 in the oldest and the others in the middle age group.
- *Education:* Education is split in primary, secondary, and tertiary education, along the lines of the re-weighting process, and to be able to compare the results internationally. Respondents do not give their income in numbers but are asked to choose one of 20 income categories. Using these answers, three groups with roughly the same amount of respondents, are constructed, representing lower-, middle-, and upper-income classes. The cutoffs are 1.500€ and 3.000€ respectively. In the regression models, I included only a dummy for being part of the upper-income class, to avoid too much correlation with education. However, the results do not change when including all three income classes, where the bottom income class is used as a baseline.
- *Economic ideology:* The ideology is an important factor for describing people's mobility perceptions, as Alesina, Stantcheva, et al. (2018) show. Especially views about meritocracy in society matter. Thus, the corresponding question in the survey asked people to place themselves on a range from 1 (very conservative) to 5 (very progressive), according to their economic ideology. The categories 1 and 2 and 4 and 5, were merged respectively to avoid too small groups. The emphasis on economic ideology was chosen to avoid conflicts of being politically progressive and economically conservative or vice versa and because economic ideology is a better proxy for those values, that matter for perceptions of intergenerational mobility such as meritocracy.

Data Quality

To ensure data quality, I conducted several quality checks. First, I used an attention check question available in the dataset to detect distracted respondents. Berinsky, Margolis, and Sances (2014) show that such checks are effective in identifying inattentive respondents. Further, they point out that not paying attention to this problem in surveys could mitigate important systematic relationships in the data or lead to falsely rejected treatment effects. Additionally, there is evidence that these checks do not affect the respondent's answers in following questions or increase attenuation (see Berinsky, Margolis, and Sances, 2014; Kung, Kwok, and Brown, 2018). Thus, I constructed a dataset which will be called attention check dataset in the following, where all respondents who did not correctly answer the attention check question in the dataset[5] were omitted. In this way, I excluded 1428 observations, resulting in a dataset with 2772 observations. Such a large share of the dataset failing this check is comparable to some previous research, as in Berinsky, Margolis, and Sances (2014) who exclude between one-third and one-half of his observations by conducting different attention checks. However, Ballard-Rosa, Martin, and Scheve (2016) only exclude around 8% of their sample based on their attention check, which is clearly less than I exclude and indicates possible quality issues with the dataset. As Berinsky, Margolis, and Sances (2014) recommend to use more than one data check, I checked the data additionally for insufficient effort or lazy responding issues. These errors in survey data are shown to be not just random measurement errors, but could significantly bias the results (see Huang, Liu, and Bowling, 2015). Thus, I formulated some criteria for the question about perceptions of intergenerational mobility, which the respondent's answers had to fulfill to remain in the dataset. These criteria are similar to those used by Alesina, Stantcheva, et al. (2018) for the same survey question. First, I omitted all individuals who answered that all poor children would become rich, or all rich children would become poor, which corresponds to 39 observations. Further, everyone, who put the same number in the field for poor children staying poor and poor children becoming rich, and vice versa for rich children, was eliminated as well. This procedure should identify everybody who just assigned the same number of people to any rung on the right side of the intergenerational mobility question, presented in figure 1. This reduced the full sample by 1200 observations, resulting in exactly 3000 observations. Again, the share of observations which are lost is relatively high. Reassuringly, Alesina, Stantcheva, et al. (2018) present a description of similar criteria of their intergenerational mobility question in their online appendix and in sum the affected observations amount to around a quarter of their observations as well.[6] This dataset will, in the following, be referred to as the lazy responding dataset. Finally, I combined these two checks and constructed a restrictive dataset, which excludes all observations which do not pass any of the two data checks. This restrictive dataset, which comprises 2133 observations, is used for all following calculations, if not stated otherwise.

In spite of the significantly increased quality of the remaining sample, there are some issues which have to be accounted for when such a big share of the original observations fails the data checks. Berinsky, Margolis, and Sances (2014) emphasise that the passing of these tests is not randomly distributed among the individuals in the sample, but instead correlated with different important characteristics such as age, gender, and race. Therefore, these data checks can be seen as a trade-off between internal and external validity. On the one hand, they increase internal validity by improving the quality of the data. On the other hand, they reduce external validity, because a significant share of the target population is probably not appropriately represented in the reduced sample and excluded from the analysis. To account for these problems, I calculated all results of the following work for all four different data sets. Differences between those are analysed in section 6. Reassuringly, the results do not differ considerably between all four data sets. Additionally, after reducing the dataset, 49% of the observations result from the first wave, and

[5]"We are interested in your opinion to different topics, such as colours. To show that you read this far, please select "red" and "green" out of the following possibilities. Do not pay attention to the question and just choose the two stated possibilities. What is your favourite colour?" - pink, red, green, white, black, blue

[6]However, they only exclude a part of these observations, because they do not take all their stated criteria into account. Further, they do not elaborate on the reasons for this decision.

51% of respondents were treated. The treatment and control group are divided equally between both rounds. In tables 9 to 12, the differences in important variables in the different data sets can be seen. The attention check results in a slightly more progressive, less urban, and richer dataset. The lazy responding data check only reduces the share of less progressive people in the dataset, while the other characteristics stay similar, compared to the full dataset. The differences in the variables education, gender, and age are nonexistent because the weights adjust the data sets with respect to these margins. The differences in the mobility variables between the different data sets can as well be seen in tables 9 to 12. The variance of all variables increases for the bigger data sets. Additionally, the bigger data sets seem to be more optimistic than the restrictive data set. The mean and median of the mobility variables increase, while the mean and the median of the persistence variables decrease for the bigger data sets. This difference is most pronounced for the attention check and full data sets, which indicates that the lazy responding quality check omits observations, which are on average more optimistic. This is driven by those observations, which assign the same number of people to every rung on the ladder, and which are omitted due to the assumption that this answer results from lazy responding and does not represent their actual perceptions.

Table 5 shows the proportions of relevant groups of society in both waves and the Austrian population to check the representativity of the sample. The differences seem to be small, but survey participants are slightly younger and more educated than the overall population, which is a known problem in online surveys. However, this can partly be counteracted by using post-stratification weights, which I calculated for the final sample along the lines of the three variables, shown in table 5. Thus, the sample is representative of the Austrian population with respect to age, gender, and education. However, I cannot control for sample selection based on other characteristics, like income, or unobservable variables. Further, non-sampling errors such as coverage errors or different probabilities of being sampled for different subgroups of society cannot be accounted for. Additionally, table 6 shows the characteristics of the sample for the full dataset, before the quality checks were conducted. The original sample was slightly older, and thus fitted the age distribution of the target population better than the restrictive dataset. Additionally, the higher share of respondents with lower education in the full dataset does as well match the Austrian population better. Thus, the trade-off between internal and external validity of data checking, as Berinsky, Margolis, and Sances (2014) emphasise, is definitely an issue and has to be taken into account.

Table 5: Characteristics of the sample, restrictive dataset

	total	wave 1	wave 2	population
men	48.3	49.7	46.8	49.2
women	51.7	50.3	53.2	50.1
under 35	28.9	24.7	33.3	29.0
35 - 55	42.2	43.3	41.0	33.7
over 55	28.9	32.0	25.7	37.3
primary education	42.2	44.4	39.9	52.7
secondary education	35.8	34.6	37.2	30.2
tertiary education	22.0	21.0	23.0	17.1

Columns 1 to 3 show unweighted proportions for the reduced sample. The data for the Austrian population was taken from Statistik Austria and was further used to re-weight the sample.

Table 6: Characteristics of the sample, full dataset

	total	wave 1	wave 2	population
men	49.5	50.0	48.9	49.2
women	50.5	50.0	51.1	50.1
under 35	26.2	23.5	29.0	29.0
35 - 55	41.7	41.3	42.0	33.7
over 55	32.1	35.1	29.0	37.3
primary education	48.8	49.6	48.0	52.7
secondary education	32.7	32.4	33.0	30.2
tertiary education	18.5	18.0	19.0	17.1

Columns 1 to 3 show unweighted proportions for the reduced sample. The data for the Austrian population was taken from Statistik Austria and was further used to re-weight the sample.

Furthermore, even though the treatment was shown randomly, systematic differences between the control and the treatment group could arise and bias the treatment results. However, as can be seen in table 7, the groups are very similar. There are slightly more conservative respondents in the treatment group, which could understate the treatment effect. Additionally, there seem to be fewer people living in urban surroundings. However, a regression on the probability of being in the treatment group shows no significant effects for all the variables shown in table 7. This confirms the random nature of the treatment and justifies causal interpretations of the treatment effects.

Table 7: Control and Treatment group

	total	control group	treatment group
men	49.2	48.5	49.8
women	50.8	51.5	50.2
under 35	29.0	28.4	29.7
35 - 55	33.7	35.3	32.2
over 55	37.3	36.4	38.1
primary education	52.7	51.0	54.3
secondary education	30.2	31.4	29.1
tertiary education	17.1	17.7	16.6
progressive	27.6	27.5	27.6
middle	54.6	56.1	53.2
conservative	17.9	16.4	19.2
lower class	33.8	34.5	33.2
middle class	40.5	41.4	39.7
upper class	25.7	24.2	27.2
exp. no mobility	39.7	39.8	39.5
exp. upward mobility	21.0	19.9	22.1
exp. downw. mobility	39.3	40.2	38.4
urban	36.6	38.2	35.1
semi-urban	24.2	23.4	24.9
thinly populated	39.2	38.4	40.0

The table shows weighted proportions for the restricted dataset.

Table 8: Intergenerational Mobility Perceptions among different subgroups

	Q1Q5	Q1Q1	Q5Q1	Q5Q5
total	6.11	46.35	4.11	61.69
male	5.85	47.08	4.37	61.85
female	6.35	45.64	3.86	61.53
under 35 years	6.44	46.57	4.90	59.39
35-55 years	6.41	46.81	4.30	63.01
over 55 years	5.57	45.77	3.32	62.28
primary education	7.51	42.70	5.11	58.94
secondary education	4.84	49.89	3.04	64.61
tertiary education	4.03	51.33	2.92	65.00
lower class	6.89	44.65	4.40	59.69
middle class	6.06	46.90	3.77	63.56
upper class	4.24	51.08	3.61	64.20
urban	5.26	47.95	3.55	64.33
semi-urban	6.19	46.26	3.78	61.77
thinly populated	6.71	44.84	4.85	59.07
progressive	5.48	52.09	3.45	66.25
middle	6.52	43.95	4.42	59.89
conservative	5.80	44.83	4.17	60.14

The table shows weighted means of the mobility variables in the specific subgroups of the restrictive dataset.

Table 9: Descriptive statistics of important variables in the restrictive dataset

A. Continuous variables					
	Min.	Mean	Median	S.D	Max.
Q1Q5	0.0	6.1	1.0	12.4	93.0
Q1Q1	0.0	46.3	50.0	26.0	100.0
Q5Q1	0.0	4.1	0.0	9.3	98.0
Q5Q5	0.0	61.7	70.0	26.8	100.0
Q1Q45	0.0	12.9	5.0	18.3	95.0
Q5Q12	0.0	9.4	3.0	15.7	100.0
B. Categorical Variables					
	Share	No. of Obs.			
men	49.2	2133			
women	50.8	2133			
under 35	29.0	2133			
35 - 55	33.7	2133			
over 55	37.3	2133			
primary education	52.7	2133			
secondary education	30.2	2133			
tertiary education	17.1	2133			
progressive	27.6	2133			
middle	54.6	2133			
conservative	17.9	2133			
lower class	33.8	2133			
middle class	40.5	2133			
upper class	25.7	2133			
urban	36.6	2072			
semi-urban	24.2	2072			
thinly populated	39.2	2072			

Part A. shows weighted statistics of the continuous variables in the restrictive dataset. Part B. shows the weighted relative frequencies of the categorical variables in the restrictive dataset and the corresponding number of observations.

Table 10: Descriptive statistics of important variables in the lazy responding dataset

A. Continuous variables					
	Min.	Mean	Median	S.D	Max.
Q1Q5	0.0	7.3	1.0	13.5	93.0
Q1Q1	0.0	44.2	45.0	26.5	100.0
Q5Q1	0.0	5.4	0.0	11.2	99.0
Q5Q5	0.0	59.1	60.0	28.2	100.0
Q1Q45	0.0	15.0	7.0	20.2	100.0
Q5Q12	0.0	11.6	4.0	18.2	100.0
B. Categorical Variables					
	Share	No. of Obs.			
men	49.2	3000			
women	50.8	3000			
under 35	29.0	3000			
35 - 55	33.7	3000			
over 55	37.3	3000			
primary education	52.7	3000			
secondary education	30.2	3000			
tertiary education	17.1	3000			
progressive	26.2	3000			
middle	55.9	3000			
conservative	17.9	3000			
lower class	34.3	3000			
middle class	40.7	3000			
upper class	25.0	3000			
urban	37.3	2904			
semi-urban	24.8	2904			
thinly populated	37.8	2904			

Part A. shows weighted statistics of the continuous variables in the lazy responding dataset. Part B. shows the weighted relative frequencies of the categorical variables in the lazy responding dataset and the corresponding number of observations.

Table 11: Descriptive statistics of important variables in the attention check dataset

A. Continuous variables					
	Min.	Mean	Median	S.D	Max.
Q1Q5	0.0	10.0	2.0	16.8	100.0
Q1Q1	0.0	39.7	40.0	27.6	100.0
Q5Q1	0.0	7.0	1.0	13.0	100.0
Q5Q5	0.0	54.4	55.0	30.0	100.0
Q1Q45	0.0	19.0	10.0	23.5	100.0
Q5Q12	0.0	14.6	5.0	20.4	100.0
B. Categorical Variables					
	Share	No. of Obs.			
men	49.2	2772			
women	50.8	2772			
under 35	29.0	2772			
35 - 55	33.7	2772			
over 55	37.3	2772			
primary education	52.7	2772			
secondary education	30.2	2772			
tertiary education	17.1	2772			
progressive	26.5	2772			
middle	55.3	2772			
conservative	18.2	2772			
lower class	33.6	2772			
middle class	41.1	2772			
upper class	25.3	2772			
urban	36.8	2692			
semi-urban	25.2	2692			
thinly populated	38.0	2692			

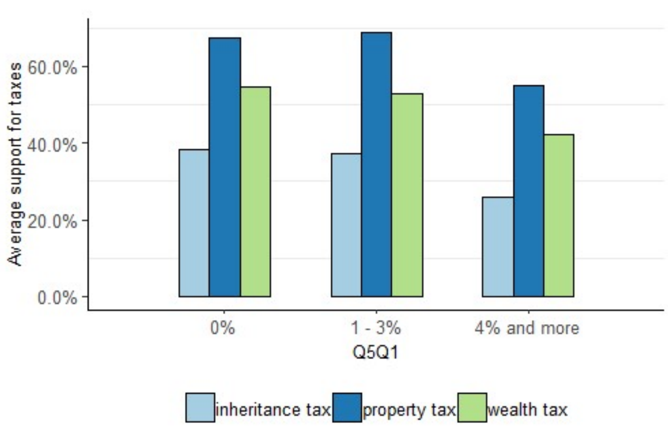
Part A. shows weighted statistics of the continuous variables in the attention check dataset. Part B. shows the weighted relative frequencies of the categorical variables in the attention check dataset and the corresponding number of observations.

Table 12: Descriptive statistics of important variables in the full dataset

A. Continuous variables					
	Min.	Mean	Median	S.D	Max.
Q1Q5	0.0	11.8	5.0	17.9	100.0
Q1Q1	0.0	36.9	30.0	27.6	100.0
Q5Q1	0.0	8.9	1.0	15.1	100.0
Q5Q5	0.0	50.5	50.0	30.6	100.0
Q1Q45	0.0	20.0	10.0	25.0	100.0
Q5Q12	0.0	17.6	8.0	22.6	100.0
B. Categorical Variables					
	Share	No. of Obs.			
men	49.2	4200			
women	50.8	4200			
under 35	29.0	4200			
35 - 55	33.7	4200			
over 55	37.3	4200			
primary education	52.7	4200			
secondary education	30.2	4200			
tertiary education	171	4200			
progressive	25.1	4200			
middle	56.8	4200			
conservative	18.1	4200			
lower class	34.8	4200			
middle class	40.5	4200			
upper class	24.7	4200			
urban	37.5	4066			
semi-urban	25.5	4066			
thinly populated	37.0	4066			

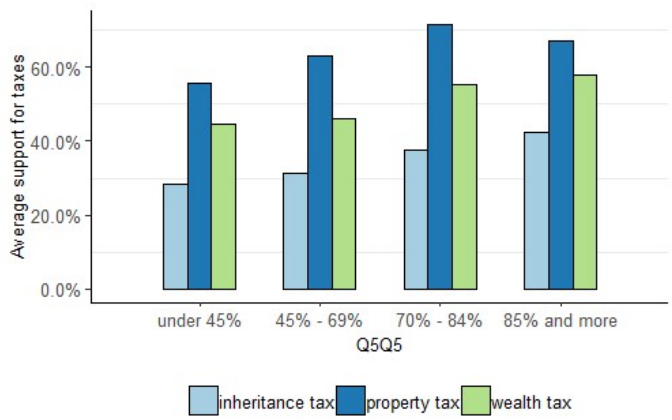
Part A. shows weighted statistics of the continuous variables in the full dataset. Part B. shows the weighted relative frequencies of the categorical variables in the full dataset and the corresponding number of observations.

Figure 11: Demand for redistribution by downward mobility perceptions



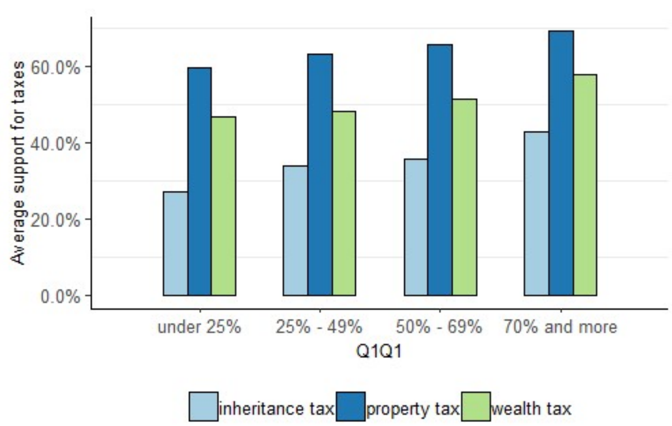
Interpretation example: Around 70% of respondents, who state that less than 4% of children from the top quintile will leave it when grown up, support the property tax, while only around 55% of those, who answer 4% or more, do. Due to the small variance of the downward mobility perception variable, it can be seperated in 3 catagories only.

Figure 12: Demand for redistribution by top persistence perceptions



Interpretation example: Around 30% of respondents, who state that less than 45% of children from the top quintile will stay there when grown up, support the inheritance tax, while around 40% of those, who answer 85% or more, do.

Figure 13: Demand for redistribution by bottom persistence perceptions



Interpretation example: Around 50% of respondents, who state that less than 25% of children from the bottom quintile will stay there when grown up, support the wealth tax, while around 60% of those, who answer 70% or more, do.

Robustness checks

The first robustness check will be to change the definition of the up- and downward mobility perception variables. Upward mobility will be defined as the number of children from the bottom quintile expected to reach the 5th or the 4th quintile and respectively downward mobility the number of those children from the top ending up in the 1st or the 2nd quintile. Using these wider mobility measures leads to a bigger variance in the dependent variable, which helps to identify effects and reduce the weight of outliers in the data. Subsequently, I will change some definitions and quality criteria on which my final sample - the exact process is explained in the next section - was based to check for consistency of the results in these different data sets. Finally, I can utilize the information from the two waves of the survey to monitor differences between those. The time difference between the two waves is slightly more than half a year, which should not result in major changes in the public opinion about this topic. However, there are slight differences in the placement of some questions and the general pool of survey questions between the waves. Thus, differences in the results between the waves could as well partly result from these. To control for these differences in the regression models, I included wave fixed effects in every regression.

Mobility perception variables

In the following, the upward and downward mobility variables are substituted with less extreme measures in equation 1 to test hypotheses 1 and 2 more thoroughly. Thus, for upward mobility, not only those poor children who are thought to reach the richest quintile but also those who reach the second richest quintile are counted as being upwardly mobile. For downward mobility, the same holds with the poorest and the second poorest quintile. This results in more variation in the dependent variable and does not only capture the most extreme answers, which can be seen in table 9.
As can be seen in table 13, the wider mobility perception variables, Q1Q45 and Q5Q12, show significant effects as well but they are smaller than for the more extreme measures.

Table 13: Effects of mobility perceptions on policy preferences

	Dependent variable:			
	wealth tax	inheritance tax	property tax	log(capital gains tax)
	(1)	(2)	(3)	(4)
log(Q1Q45)	-0.011^{***}	-0.012^{***}	-0.008^{***}	-0.035
	(0.003)	(0.003)	(0.003)	(0.036)
log(Q5Q12)	-0.016^{***}	-0.015^{***}	-0.012^{***}	-0.027
	(0.004)	(0.004)	(0.004)	(0.036)
Observations	1,836	1,937	2,072	1,781

Note: *p<0.1; **p<0.05; ***p<0.01

All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology, urbanisation and the wave. The first three regressions are weighted logistic regressions and the last one a normal linear regression. Coefficients in the first three columns are average marginal effects. White's heteroskedasticity-robust standard errors (only for column 4) are reported in parentheses. The estimates for the different mobility perception variables result from separate regression models due to the high correlation among them. The differences in observations per model result from item non-response of the dependent variables and the independent variable urbanisation.

In table 14, we see the treatment effects on the wider mobility variables. The persistence variables are the same as in table 5 and are just included for comparison. However, the treatment effect on upward mobility increases significantly in size. Instead of decreasing the perceived share of poor children becoming rich by approximately 20%, it reduces the share for the two top quintiles by nearly 30%. Nevertheless, the treatment effect for downward mobility is still not significantly different from 0. Considering the increased variance resulting from the new variable, the argument of little variation in the dependent variable gets weaker, especially as the variation in the downward mobility variable is now bigger than for the original upward mobility variable (Q1Q5), see table 9. This could be evidence that people do not react to information when considering downward mobility and only adjust their beliefs in upward mobility and persistence at the bottom as well as at the top. Regarding the lack of literature analysing effects on downward mobility perceptions, this could be of great interest to pursue further.

Table 14: Treatment effects on alternative mobility variables

	Dependent variable:			
	log(Q1Q45)	log(Q1Q1)	log(Q5Q12)	log(Q5Q1)
	(1)	(2)	(3)	(4)
treatment	-0.270^{**}	0.129^{***}	-0.017	-0.024
	(0.118)	(0.033)	(0.129)	(0.067)
Observations	2,072	2,072	2,072	2,072

Note: *p<0.1; **p<0.05; ***p<0.01

All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology and the wave. White's heteroskedasticity-robust standard errors are reported in parentheses. The differences in observations between the whole restrictive dataset and the models result from item non-response of the independent variable urbanisation.

Sample Composition - Data Checks and Waves

As described in section 3, I excluded nearly half of the observations due to quality checks. Thus, an analysis of how much the results change through this process is essential for the interpretation of my results. In the following, the above calculations are repeated with the lazy responding, the attention check, and the full dataset. The first one including the lazy responding checks, but not the attention check, the second one vice versa and the last one comprising the whole dataset.

Concerning the effects of mobility perceptions on policy preferences, the results stay very robust. The effects for Q1Q5 stay significant, but get smaller for all policy variables in the bigger datasets. The effects for Q1Q1 stay the same for the inheritance and the property tax and get significant for the wealth tax, even if the size of the coefficients is very small. The coefficients for Q5Q5 stay mostly significant as well, but are very small, as in the restrictive dataset. The effects for Q5Q1 are, however, less robust. They turn insignificant for the wealth tax in the full sample and the inheritance tax in all bigger samples, and get smaller for the property tax and the wealth tax in the lazy responding and the attention check dataset. The effects for Q1Q45 and Q5Q12 react to the changes in the dataset in the same way as the effects for Q1Q5 and Q5Q1. Further, the results for the treatment effects can be seen in tables 15 and 16.

Table 15: Treatment effects on mobility perceptions in the different data sets

	Dependent variable:					
	log(Q1Q5)	log(Q1Q1)	log(Q5Q1)	log(Q5Q5)	log(Q1Q45)	log(Q5Q12)
	(1)	(2)	(3)	(4)	(5)	(6)
restrictive dataset						
treatment	-0.180^{**}	0.117^{***}	-0.026	0.077^{***}	-0.270^{**}	-0.017
	(0.082)	(0.034)	(0.068)	(0.022)	(0.118)	(0.129)
Observations	2,072	2,072	2,072	2,072	2,072	2,072
lazy responding dataset						
treatment	-0.143^{*}	0.133^{***}	-0.037	0.074^{***}	-0.208^{**}	-0.023
	(0.074)	(0.032)	(0.070)	(0.024)	(0.100)	(0.121)
Observations	2,904	2,904	2,904	2,904	2,904	2,904
attention check dataset						
treatment	-0.203^{**}	0.131^{**}	-0.099	0.116^{***}	-0.281^{**}	-0.102
	(0.101)	(0.065)	(0.091)	(0.039)	(0.123)	(0.142)
Observations	2,692	2,692	2,692	2,692	2,692	2,692
full dataset						
treatment	-0.150^{*}	0.115^{**}	-0.071	0.080^{**}	-0.211^{**}	-0.067
	(0.083)	(0.059)	(0.083)	(0.038)	(0.097)	(0.121)
Observations	4,066	4,066	4,066	4,066	4,066	4,066

Note: *p<0.1; **p<0.05; ***p<0.01

All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology, urbanisation, and the wave. White's heteroskedasticity-robust standard errors are reported in parentheses. The differences in observations between the whole data sets and the models result from item non-response of the independent variable urbanisation.

In the dataset with lazy responding checks only, the results for mobility perceptions remain similar, also for the more general variables described above. However, the treatment effects on wealth tax becomes slightly smaller but stays significant. For the dataset, which only omits those observations from the full dataset, which fail the attention check, the treatment effects for the mobility variables and support for the wealth tax get stronger than in the restrictive dataset. When considering the full dataset, the results for mobility perceptions are slightly smaller for the upward mobility variables and very similary in size for the others. They all stay significantly different from 0, except for the effects on Q5Q1 and Q5Q12 which are not significant in the restrictive dataset as well. While the treatment effect on the wealth tax is similar in size to the effect in the restrictive dataset and still significant.

When running the analysis separately for every wave in the different data sets, the results differ somehow from the results presented above. However, the treatment effect on mobility perceptions remains mostly robust for all waves and data check variations. The effect on Q1Q1 is the strongest and most robust. Q5Q1 stays insignificant in every sample. The effects for Q1Q5 and Q5Q5 are, however, not that robust when considering the two waves separately. Here, the effect on Q1Q45 is stronger and more consistent. This could be evidence for a strong and robust treatment effect on the bottom persistence variable but not that robust for upward mobility or top quintile persistence. The effect on support for the wealth tax is only significant in wave 2 of every sample size, except for the attention check dataset, where it loses significance when calculating the effect separately for both waves. Therefore, the treatment effect on the support for the wealth tax is less robust than those on mobility perceptions.

Thus, the treatment effects on mobility perceptions are strong and robust, considering different data sets. The treatment effect on the wealth tax stays significant as well and thus can also be considered robust, however it seems to be driven by wave 2.

Table 16: Treatment effects on policy preferences in the different datasets

	Dependent variable:			
	wealth tax	inheritance tax	property tax	log(capital gains tax)
	(1)	(2)	(3)	(4)
restrictive dataset				
treatment	0.061^{**}	0.000	−0.004	0.133
	(0.024)	(0.031)	(0.021)	(0.084)
Observations	1,836	1,937	2,072	1,781
lazy responding dataset				
treatment	0.035^{*}	0.004	0.005	0.081
	(0.020)	(0.026)	(0.018)	(0.067)
Observations	2,594	2,705	2,904	2,471
attention check dataset				
treatment	0.069^{***}	0.026	0.007	0.112
	(0.021)	(0.026)	(0.019)	(0.070)
Observations	2,374	2,492	2,692	2,255
full dataset				
treatment	0.051^{***}	0.020	0.013	0.077
	(0.016)	(0.022)	(0.015)	(0.054)
Observations	3,729	3,872	4,066	3,461

Note: *p<0.1; **p<0.05; ***p<0.01

All regressions include control variables for gender, age, education, being a member of the upper income class, the political ideology, urbanisation and the wave. The first three regressions are weighted logistic regressions and the last one a normal linear regression. Coefficients in the first three columns are average marginal effects. White's heteroskedasticity-robust standard errors (only for column 4) are reported in parentheses. The differences in observations per model and to the whole datasets result from item non-response of the dependent variables and the independent variable urbanisation.