

Paying for Resentment: Positional Competition, Immigration and Support for Redistribution



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ABSTRACT

This thesis tackles the question of why the poor would be willing to pay the price of less redistribution in a context of ethno-cultural heterogeneity, even if they benefit from redistribution. I propose an argument whereby there is an extent to which people perceive differences in incomes between themselves and those poorer as justified, because they simultaneously reflect and confirm their own relative social status. Redistribution, as it compresses the income distribution, challenges this social ranking, heightens the acuteness of positional competition and consequently leads to feelings of resentment towards the people that make up the competition: those poorer than oneself. Resentment then leads to willingness to sacrifice parts of ones' own material pay-offs to reduce those of the competition even more. This means that even people who are net beneficiaries of redistribution may become less supportive of it than their material calculation would predict. I also argue that people would be particularly willing to *pay for resentment* in a context of ethno-cultural heterogeneity due to immigration.

The implications of this theoretical mechanism are tested observationally with time-series cross-sectional survey data from 25 European countries between 2000 and 2019 from the ESS and the ISSP and causally by means of an online survey experiment conducted in 2018 in the UK. The results of the observational analysis suggest that support for redistribution among the poor was lower in country-years with larger recent increases in the share of foreign-born population. Moreover, this pattern is more pronounced when the share of pre-tax income of the bottom 50% was smaller. In the experiment, respondents were randomly allocated to either no vignette; information about their position in the income distribution relative to those poorer; information highlighting recent increases in immigration; or both of these two combined. The results suggest that exposure to the combined vignettes lead to lower expressed support for income redistribution.

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1.1 Motivation

Explaining what drives support for the redistribution of income from rich to poor has long been an important research agenda within the social sciences. This is hardly surprising, as in a way, redistribution of resources is at the core of what democratic systems do – or at least are expected to do – and what distinguishes them from their non-democratic counterparts (Przeworski et al., 2000). At their essence, political processes are about “who gets what, when, how” (Lasswell, 1936). Thereby, voters’ preferences should dictate the outcome of the game. As democratisation proceeds, an increasing proportion of society is included in states’ decision-making and the right to be heard expands from an elite minority to encompass the poorer masses. Consequently, a democracy is supposed to adapt the level of income redistribution to the interests of voters.

This is the basis for the standard expectation formulated by Meltzer and Richard (1981; building on Romer, 1975 and Roberts, 1977), whereby macro-inequality, by determining the median voter’s cost-benefit calculation, should positively correlate with support for and levels of income redistribution. Put simply, those who benefit from redistribution are expected to back it; and those who pay in more than they get out, oppose it. However, over the last half century, it has become clear that neither aggregate demand for income redistribution nor supply of income redistribution necessarily follow this prediction. Variation in the median voter’s interest across countries and time does not cleanly map onto changes and differences in economic inequality (Kenworthy and Pontusson, 2005; Iversen and Soskice, 2015).

Existing literature teaches us that, in a broad sense, the welfare state is sustained by, on the one hand, the material self-interest (‘Will I benefit?’) of participants of the common pool. Next to present income (Meltzer and Richard, 1981), previous literature has identified wealth assets (Ansell, 2014), exposure to risks of income loss (Moene and Wallerstein, 2001; Rehm, 2009) as well as (beliefs about) social mobility and future prospects (Piketty, 1995; Bénabou and Ok, 1998; Alesina and La Ferrara, 2005; Rueda et al., 2014) as important aspects of individuals’ own economic situation associated with attitudes towards redistribution. Moreover, the institutional design of welfare states, such as the progressivity of the tax system, types of employment protection or health care systems, has been found to condition to what extent individual economic circumstances translate into redistributive preferences (Esping-Andersen, 1990; Jæger, 2009; Gingrich and Ansell, 2012; Beramendi and Rehm, 2016).

On the other hand, the welfare state is also sustained by social preferences and feelings regarding the other participants of the common pool (‘How do I feel about others that benefit?’). These feelings have been linked to altruism and inequality aversion (Fehr and Schmidt, 1999; Dimick et al., 2018), deservingness and reciprocity (Alesina and Angeletos, 2005; Habyarimana et al., 2009; Cavaillé, 2015) and social affinity (Alesina and Glaeser, 2004; Lee et al., 2006; Shayo, 2009). Within this last strain of literature, particular attention has been devoted to the role of ethno-cultural heterogeneity – including the one stemming from increased immigration. Many of the arguments tend to focus on a hypothesised adverse effect through out-group bias of diversity on national solidarity and the willingness of the citizenry to “accept [the] strains of commitment” (Banting and Kymlicka, 2017, 1).

This short overview of the research field shows that a large and rich body of work has developed around identifying and explaining deviations of individual-level support for income redistribution from strict material self-interest in established, advanced democracies. With this, the aim is to account for departures of aggregate support for redistribution from the above mentioned standard expectation. However, research into these two pillars of redistributive preferences – material self-interest and social preferences – has been developing rather independently of each other, treating them often as additive rather than interactive. Therefore, explanations of why those who benefit from more redistribution do not always prefer more redistribution remain incomplete

and unsatisfying, as does understanding the role of ethno-cultural heterogeneity in welfare state support. If out-group bias had no impact on material calculations, it should not matter which kind of competition, native-born or foreign-born, potentially threatens people’s material prospects. And, conversely, if material calculations did not feed into attitudes towards immigrants, arguments representing them as free riders and abusing the welfare state would not have much leverage.¹ Therefore, the core motive of this thesis is to advance the understanding of how individuals’ material and social calculations can interact to affect support for the redistribution of incomes, especially under the pressure of immigration.

This is not only important from an academic standpoint, but also highly relevant for trying to grasp the political consequences of recent socio-economic developments in a large number of developed democracies. A significant and relatively steady rise in economic inequality can be observed in most developed countries over the last decades, driven by an uneven growth of income across the distribution (c.f. Alvaredo et al., 2018), before and, to a lesser extent, after redistribution. Figure 1.1 illustrates this phenomenon for 16 European countries from 1980 onwards. The countries are grouped by the welfare regime typologies based on Esping-Andersen (1990) and Ferrera (1996).² Based on data taken from the Word Inequality Database (Blanchet et al., 2021), the figure shows the upper thresholds of each decile in terms of pre-tax gross income (left) and disposable income (right) in constant purchasing power parities-converted Euros. All four welfare regimes present a pattern of a ‘fanning out’ of the income distribution from the top. While the lowest decile’s line appears nearly flat, the lines are increasingly upwards sloping the higher the decile. In particular, among the social-democratic and liberal welfare states, the richest 10% earned at least nearly double before tax in the last decade than they did in 1980. This development is less extreme among conservative welfare states where the gaps between the pre-tax income deciles was already higher to begin with. The pattern is a bit more muted among Southern welfare states. The distribution of disposable income is clearly more compressed, showing the impact of redistribution. And yet, the same fanning-out pattern is visible here, too.

Another perspective on this situation can be provided by looking at the development

¹A similar point is made by Cavaillé and Ferwerda (2017, 25-26).

²These typologies are very similar when it comes to Western European countries – save Switzerland which is classified as liberal by Esping-Andersen and as Bismarckian by Ferrera. The main difference in the latter classification is the addition of the Southern welfare state as separate category.

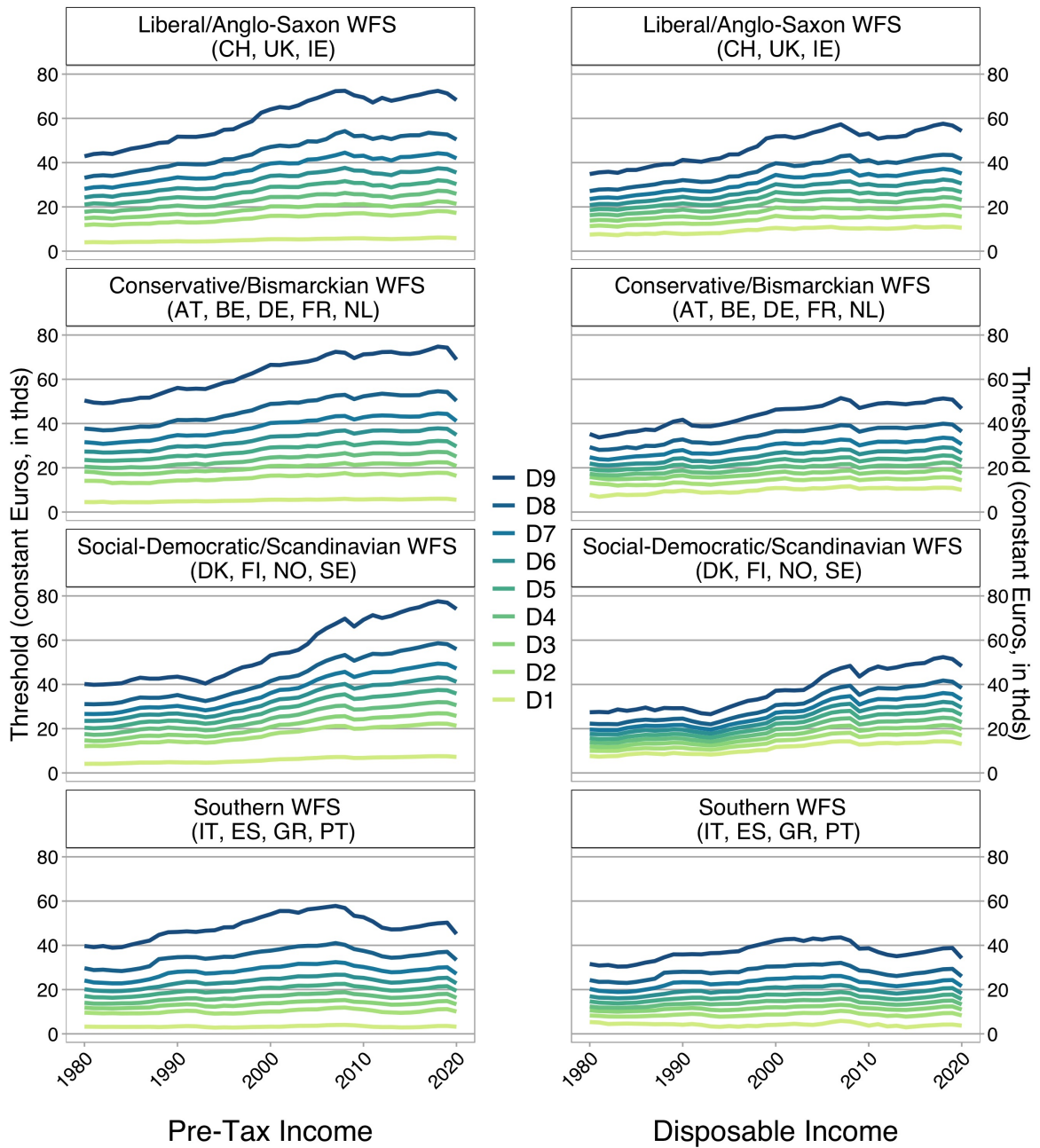


Figure 1.1: Income Distributions over 40 Years and across 16 European Countries
Source: World Inequality Database, threshold income series. Each line indicates the maximum pre-tax and disposable income received within each decile, respectively.

of the income shares of the top 10% relative to the bottom 50%. Figure 1.2 displays this for Germany, France, Sweden and the United Kingdom. Sweden, as the emblematic social-democratic welfare state (Esping-Andersen, 1990), is the only country of the four characterised by more equal and nearly overlapping shares until the beginning of the new millennium. However, even there, the gap between the two increases to the benefit of the top 10% hereafter. The divergence between the two groups is particularly

dramatic in Germany, where the difference in shares nearly tripled between the mid-90s and the late 2010s. In France and the United Kingdom, there has been a significant divergence of both shares in the first 20 years, after which the share of the bottom 50% changes only minimally in the last 20 years. But despite these relatively universal dynamics, and in particular a relative impoverishment of the lower income classes, this does not seem to be clearly followed by equivalent changes in support for more income redistribution.

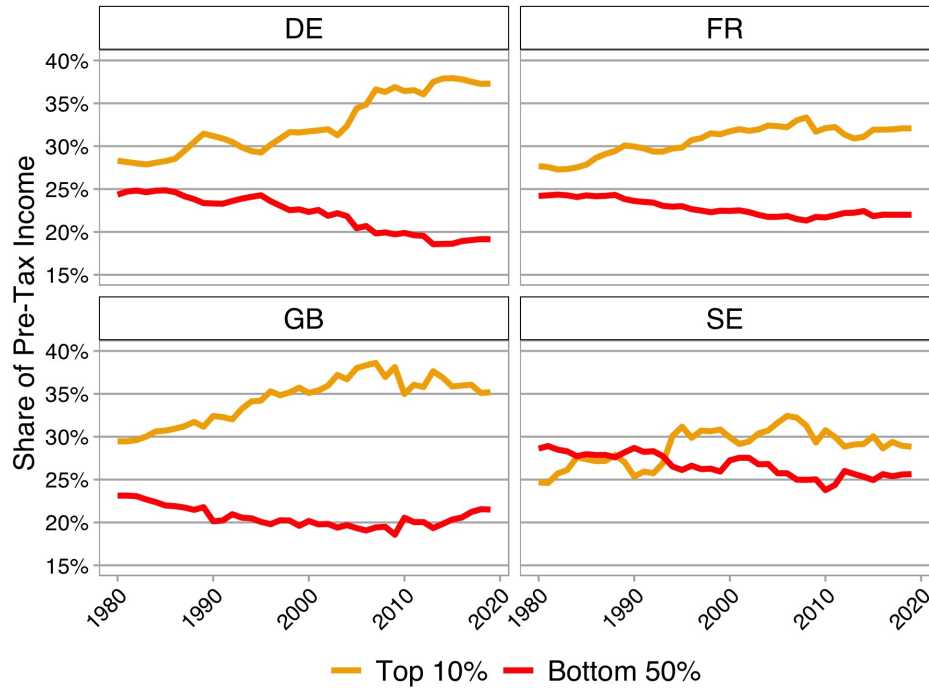


Figure 1.2: Shares of Pre-Tax Income in four European Countries
Source: World Inequality Database, shares of income series.

Using survey data from the European Social Survey (ESS) and the International Social Survey Programme (ISSP), Figure 1.3 illustrates this observation for the same four countries highlighted above. It shows the average support for redistribution by the government for respondents in the bottom 50%, middle 40% and top 10% of equivalised income. The line for the bottom 50% (in red) is remarkably flat in Sweden. In Germany, which has seen the highest decrease in the share of income of the bottom 50%, it shows a slightly upwards sloping trend between the beginning of the 2000s until 2010, after which it plateaus. Conversely, in France there appears to be a downwards trend between the mid 2000s until the mid 2010s. In the UK, the trend follows a very shallow U-curve. Two points are worth making based on these observations. First, the relative ranking of the three income groups is consistent with the standard expectation that

support for redistribution declines as income goes up. However, the extent of the differences between income groups is not consistent across countries and time. Second, the increasing income differences and diverging income shares between the rich and poor do not appear to be associated systematically with an increase in support for redistribution at the bottom of the income distribution.

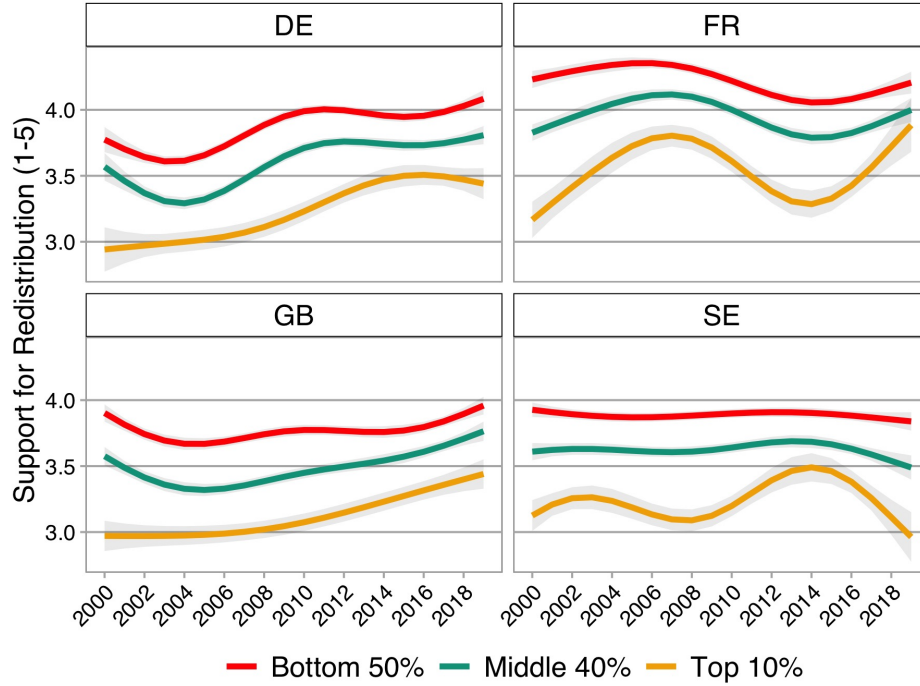


Figure 1.3: Average Support for Redistribution in four European Countries

Source: ESS & ISSP. Illustration based on the results of a country-specific Generalised Additive Model (GAM) with 5 knots. The income groups are constructed by using the respondents' self-reported household income, dividing it by the square root of household size and defining the relevant percentile thresholds per year and country. The dependent variable is measured on a 1-5 Likert scale by agreement with the statement: "The government should take measures to reduce differences in income levels".

As introduced at the beginning of this chapter, a prominent line of research argues that ethno-cultural heterogeneity moderates the relationship between inequality and support for redistribution. And indeed, over the last decades, immigration has increasingly become a 'hot topic' in political debates of many developed countries. Often, detractors of immigration claim that immigrants pose an existential threat to the welfare state and public services. Figure 1.4 presents a piece of anecdotal evidence emblematic of this kind of discourse. This poster from the then *Front National* (FN) – now called *Rassemblement National* (RN) – was part of a series of campaign tracts which was launched in late 2016 and widely shared by prominent party figures on social

media. These tracts always followed the same structure: a person is shown from the back (with a name, here ‘Pierre’, suggesting strongly that they were ethnically white French), whose situation is described as economically vulnerable. This is followed by the phrase: “unfortunately for them, they are not a migrant”, accompanied by a short description of what the state supposedly offers asylum seekers or migrants in terms of benefits (e.g. direct cash benefits or social housing).³ The relatively straightforward message of the poster seeks to elicit indignation about the implication that the state helps poor French people less than migrants and asylum seekers – so much so that the latter are better off than native-born citizen.



Figure 1.4: 2016 Campaign Poster by the FN

Source: Facebook post by the FN’s David Racheline, who was at the time Senator and Mayor of Fréjus, and is now vice-president of the Rassemblement National. The post is accompanied by the caption “Our farmers are desperate, in debt, without decent incomes. But our leaders are at the bedside of migrants... #InTheNameOfThePeople.” The poster reads: “Pierre, retired farmer, lives with 284 Euros per month. Unfortunately for him, Pierre is not a migrant. [In the bottom left white box:] Asylum seekers can receive from the state a monthly allowance of 330 Euros.”

One year later, in the 2017 Presidential Election, the FN’s candidate Marine Le Pen made it past the first round before losing to centrist Emmanuel Macron. She

³These statements about benefits given to migrants and asylum seekers (often referred to interchangeably by the FN) and the lack of equivalent benefits to native born are either misrepresentations or inaccurate (Le Monde http://www.lemonde.fr/les-decodeurs/article/2016/11/07/les-intox-du-fn-sur-les-privileges-des-migrants-face-aux-francais_5026857_4355770.html Last accessed 15/09/2021). For instance, all retired people in France can benefit at the least from a solidarity allowance for the elderly and therefore receive at minimum about 800 Euros per month, which is much more than the 284 euros that Frenchman ‘Pierre’ supposedly is living on (Official website of the French Public Administration. <https://www.service-public.fr/particuliers/vosdroits/F16871?lang=en>. Last accessed on: 15/09/2021).

campaigned with a manifesto that wanted to re-implement the *defiscalisation* (translating to ‘detaxation’) of overtime hours;⁴ “reduce income tax by 10% on the first three tax brackets” (FN, 2017, 12);⁵ more broadly, “put our public finances back in order by putting an end to bad public spending (particularly those linked to immigration and the European Union) and by fighting social and tax fraud” (FN, 2017, 8); while, at the same time wanting to “introduce a purchasing power bonus for low incomes and small pensions (for incomes up to 1,500 euros per month), financed by a 3% social contribution on Imports” (FN, 2017, 9). These policy proposals are a puzzling mix. They are clearly decrying the burden immigrants supposedly unfairly place on the welfare state. At the same time, besides the introduction of some minor cash benefits, the measures they propose to make “taxation more just” (FN, 2017, 12) reveal the wish to scale back redistribution by reducing taxes and increasing the share of market income relative to benefits in people’s disposable income.

These kind of ideas seemed to also sieve through to French voters. For instance, the popular infotainment television programme *Quotidien* broadcasted a segment interviewing likely FN voters in March 2017.⁶ These people expressed frustration at the fact that ‘everything is done here to keep us out of work’ and that they would rather have a job and not have to be helped by the state. More broadly, the negatively connoted buzzword *assistanat* (translating to ‘life under assistance’) has had a steady role in French political discourse at least since Sarkozy’s 2007 Presidential campaign.⁷ A survey from March 2017 found that 71% of the respondents deemed that the fight against the *assistanat* ought to be a priority.⁸ More recently, far-right ex-journalist

⁴I.e. exempting overtime pay from income tax and some social contributions for both employers and employees. This measure has been something of a political ‘hobbyhorse’ of the French conservative right for a while. It was first introduced in 2007 under conservative President Sarkozy in the context of his programme “work more to earn more”, before being repealed under socialist President Hollande (Askenazy, 2013).

⁵In 2017, the first bracket (up to 9,710 euros p.a.) were taxed at 0%, the second (9,710 to 26,818 euros p.a.) at 14%, and the third bracket (26,818 to 71,898 euros p.a.) at 30% (Official website of the general directorate of public finances).

⁶Quotidien avec Yann Barthes: *Des jeunes abandonnés prêts à voter FN*. Broadcast on 14/03/2017. <https://www.tfl.fr/tmc/quotidien-avec-yann-barthes/videos/jeunes-abandonnes-prets-a-voter-fn-1.html>. *Last accessed on 25/01/2022*.

⁷“Sarkozy et la dénonciation de l’assistanat, une vieille histoire” Article published on 15 November 2011. <https://www.nouvelobs.com/politique/election-presidentielle-2012/20111115.OBS4525/sarkozy-et-la-denonciation-de-l-assistanat-une-vieille-histoire.html>. *Last accessed on 08/01/2022*.

⁸Le Monde. “Le ‘cancer’ de l’Assistanat: Origine d’un Préjugé” Article published on 26 October 2017. https://www.lemonde.fr/idees/article/2017/10/26/les-procureurs-de-l-assistanat_5206354_3232.html *Last accessed on 10/01/2022*.

presidential hopeful Éric Zemmour, who is also campaigning for sending back “all undesirable foreigners”,⁹ has also taken up the word for himself by tweeting: “to get out of the plague of the *assistanat*, our solidarity must become national again. Work must be more remunerative than social benefits”. At the time of writing, Zemmour, a complete newcomer to active politics, is polling at 14%.¹⁰

Another example along these lines can be found in the German populist right party *Alternative für Deutschland* (AfD). Figure 1.5 shows one of the party’s campaign posters for the 2017 federal election. The four vultures sitting on a rail are intended to be evocative of welfare scroungers, who are possibly also immigrants. The same idea like the one depicted in the aforementioned campaign poster was also part of their 2021 political project on social policy, where they again re-committed to the idea that “the welfare state needs borders”¹¹ and stated more explicitly that there should be “no direct immigration into the social security systems” (AfD, 2020, 70). At the same time, according to their 2021 manifesto, they campaigned for the abolition of the inheritance tax (AfD, 2021, 36) and the replacement of unemployment benefits (so-called “Hartz IV”) with an “activating basic security”, whereby people in work pay less in contributions such that “those who work will definitely have more money at their disposal than those who do not work, but are able to work (*Lohnabstandsgebot*)”¹² (AfD, 2021, 121). The notion that earned income from employment should be higher than that of benefits, reflecting that it is ‘worth’ more, appears to be a recurring theme among this and the previous examples. On the macro-economic scale, they demanded a “return to a balanced national budget” and that “similar to the debt brake, a binding tax and levy brake is to be included in the *Grundgesetz*” (AfD, 2020, 74-75).

Certainly, these examples are of anecdotal nature. However, they speak to a broader trend among populist right wing and far-right parties. These parties seem to use the welfare state to justify an anti-immigration agenda, but they also use immigration to justify their welfare state agenda. The political discourse here does not only include calls for protection of the welfare state against immigration. It also combines those with

⁹Éric Zemmour’s programme on immigration. <https://programme.zemmour2022.fr/immigration>. *Last accessed on 10/01/2022*.

¹⁰According to the Opinionway/Kea Partners Barometer. <https://www.opinion-way.com/fr/barometre-opinionway-kea-partners>. *Last accessed on 26/01/2022*.

¹¹AfD Website - Position on Social Issues. <https://www.afd.de/sozialpolitik/>. *Last accessed on 11/01/2022*.

¹²Translating to ‘wage gap rule’.



Figure 1.5: 2017 Campaign Poster by the AfD

Source: Horizont (a German trade magazine for marketing and media). <https://www.horizont.net/galerien/Populistisch-nicht-populaer-3255>. Last accessed on 03/10/2021. The poster reads: “Welfare State? Needs Borders!”. In the bottom left is written their official slogan for the election: “Dare yourself, Germany!”

more or less explicit calls to limit income and wealth redistribution in general. They seek to discredit the welfare state itself by using the spectre of immigration. As such, these examples do not fit neatly into the classical type of ‘welfare state chauvinism’. This generally involves advocating that “the welfare services should be restricted to ‘our own’” (Andersen and Bjørklund, 1990, 212), but with an explicit “move to the defense of income redistribution ... [and] protection from the risks of labor markets” (Kitschelt and McGann, 1995, 22). The contemporary political debates do retain a distinct flavour of ‘welfare chauvinist’ resentment directed at immigrants. However, at the same time, the resentment appears to be also directed at the welfare state itself and its redistributive principles. Their stance on the welfare state could more adequately be described as chauvinistic welfare state retrenchment or as modernised “balanced-budget conservatism” (Calavita, 1996). A similar analysis was made by French journalist Bernard Guetta when speaking about the results of the Italian elections in June 2018:

In all these new nationalist forces that have thus, everywhere, the wind in their sails, there is this mixture of Maggie Thatcher and a rejection of old parties that

no longer manage to protect the social *aquis* of their voters and to protect them from the outside world. These new forces are completely contradictory, for the retreat of taxes means the retreat of social protection and common goods; yet these new forces advance, in the face of the ever more breathless centre-right and centre-left [...].¹³

This statement might be slightly brushing over variation across countries, but the question of how increasingly economically insecure lower and lower middle classes can be convinced not just to tolerate, but also to support, tax cuts is relevant for many established democracies today.

This detour into the supply-side of redistributive politics raises important questions about the mechanisms of preference formation on the demand-side. It is particularly puzzling why some people choose to vote for parties that commit to protect the welfare state from immigrants while they also present a more or less explicit anti-redistribution agenda. In the face of the significant and near ubiquitous rise in inequality between rich and poor, it is striking that this kind of electoral messaging is thought to be effective. There is a need to better understand the kinds of feelings that this pitting of the native-born against foreign-born poor seeks to tap into. One prominent explanation is that xenophobically motivated anti-immigrant attitudes simply overpower material self-interest, as Lee et al. (2006) argue for instance. Yet, as stated above and developed in the next chapter, treating material and social motives as orthogonal dimensions in people's calculations offers an incomplete picture. If the immigration and redistribution issues were unrelated in the minds of voters, such right-wing populist parties would not go to such lengths to combine the two policy areas. To sum up, my thesis is lead by the following central question:

Research Question

Why would the poor be willing to pay the price of less redistribution in a context of ethno-cultural heterogeneity, even if they benefit from more?

¹³Segment on the public radio France Inter broadcasted on 04/06/2018. <https://www.franceinter.fr/emissions/geopolitique/geopolitique-04-juin-2018>. *Last accessed on 15/09/2018.*

1.2 The Argument in a Nutshell

In response to the question above, the argument I present proposes a demand-side focused, individual-level mechanism of *how* social considerations interact with material considerations to affect individuals’ willingness to support the redistribution of income. I argue that the value, or satisfaction, people derive from their own material pay-offs depends in part on the comparison with other people’s pay-offs – especially if these ‘others’ are noticeably socially and culturally different. Wanting to preserve the advantageous position relative to those ranked below can therefore be grounds for opposing more redistribution, because they fear that the demarcation would get lost or become more blurry. Individuals become willing to internalise the costs.

With this argument, I build on behavioural economics research concerned with the effect of reference points, or endowments, on what individuals perceive as ‘gains’ or ‘losses’, and why these may not always be the same as absolute net material benefits (Kahneman and Tversky, 1979; Köszegi and Rabin, 2006). Of particular relevance here is work on the role of social contexts and social comparisons in economic decision-making, including decision-making under risk (Loewenstein et al., 1989; Trautmann and Vieider, 2011). Moreover, experimental evidence suggests that (social) reference points can have an effect on demand for redistribution (Charité et al., 2019) and for insurance (Friedl et al., 2014).

I call the theoretical mechanism *Paying for Resentment*. The choice of the word “resentment” here captures the intrinsic status-oriented interpretation of this type of inequality (Feather and Nairin, 2005) and the “[b]itter indignation at having been treated unfairly”¹⁴ that it may cause. The “paying” element reflects that in order to correct this situation, people are ready to forego some *absolute* material benefits in order to preserve (and possibly improve) their advantageous *relative* pay-off. The logic of this mechanism, which I summarise here, is fivefold.

First, people derive utility in the form of social status from maximising their position relative to those less well off.

I justify this assumption by considering that income differentials act as signals for a particular status, and also endogenously reinforce the legitimacy of social

¹⁴Source: <https://www.lexico.com/definition/resentment>. Last accessed on 10/05/2021.

ranking. While there is plenty of evidence that people do suffer from upwards comparisons (c.f. Fehr and Schmidt, 1999; Cansunar, 2021), I focus on downwards comparisons and the positional competition that ensues. The intuition here has similarities with the ‘Last Place Aversion’-mechanism presented by Kuziemko et al. (2014). However, I do not restrict it to aversion towards the last place, but towards lower rank more generally.¹⁵ According to my argument, a demarcation from those below serves to gain inwards confirmation and outward recognition of a particular social rank. Therefore, income differentials between individuals and people in the income classes below them can be perceived as *justified*.

Second, redistribution, as it compresses the income distribution, is perceived as a threat to a clear demarcation between groups.

The assumption just summarised forms the basis of the proposed reasoning behind why individuals may be less supportive of redistribution than their material self-interest would predict. With the compression of the income distribution, signals of income differences become more mixed and the social value attached to a particular income decreases. This then may cause resentment (“bitter indignation”) towards those groups who are perceived to, unfairly, catch-up with one’s own economic position. Therefore, they “put additional value on outcomes that help them to achieve their aspiration level, for instance a social comparison outcome” (Trautmann and Vieider, 2011, p.583) and demand less redistribution to the benefit of preserving one’s position relative to those below.

Third, this is more relevant for those lower down the income distribution, for whom clear downwards demarcation ‘means’ more.

Importantly, I also assume that downwards social comparisons and positional competition are not equally relevant across the income distribution. In fact, for the lower income classes, clear social boundaries can serve as an alternative source for a sense of “social dignity” (Lamont, 2000). Preserving social status will be more important to those who feel theirs is under threat (Gidron and Hall,

¹⁵Kuziemko et al. (2014) themselves concede that it is “difficult to distinguish between strict last-place aversion and a more general low-rank aversion” (p.107), yet their empirical tests allow them to “always separate last-place or low-rank aversion from [...], generally, a linear effect of initial rank” (p.107).

2017). The intuition here is that the marginal (dis-)utility from improving or worsening one's income position will be higher for those with an already lower income position.¹⁶ Therefore, the poor have more to lose from a compression of the income distribution in terms of relative position than the rich.

Fourth, this is more salient in a context of ethno-cultural heterogeneity due to immigration.

I argue that this mechanism is reinforced in a context where income differentials between an individual and those less well off appear even more justified because of socio-cultural differences. The relationship between Western countries' native-born, often ethnically white, majorities and immigrant minorities can arguably be described as one with a "generally recognized asymmetry in players' claims or obligations" (Cox et al., 2007, p.9). Whether due to economic or cultural fears, public discourse around and perceptions of immigrants have, on average, been mostly negative (Hainmueller and Hopkins, 2014). They are subject to the "common view that they are a net fiscal burden" (Burgoon, 2014, p.367) and often perceived as significantly less deserving of social assistance than native-borns (Van Oorschot, 2006). I conceive of these negative attitudes to be at least in part due to xenophobia, in-group favouritism and out-group prejudice, and that these are linked with perceptions of what a 'natural' social ordering should look like. Thereby, the salience of income differences as a signal for social distinction from others is likely to be higher in a context where the 'other' is seen as different in more than the economic dimension.

Fifth, the shape of the income distribution conditions how tight the competition is.

The hypothesised mechanism also has implications for the link between individual-level preferences over redistribution and economic inequality. Indeed, the shape of the income distribution not only determines overall, summative, inequality but also how large income differences are between closely ranked groups. If, following from the above, the importance of clear demarcation increases when

¹⁶This is analogous to income itself: earning £100 pounds more per month means more to someone earning £2,000 per month than someone earning £5,000 per month.

clear demarcation is harder to achieve, positional competition and its adverse effect on support for redistribution should become more salient in places where the income distribution is already more compressed before redistribution. If then, in such a context, immigration increases, I expect this lead to lower redistributive preference. Therefore, I hypothesise a moderating effect of inequality on the effect of immigration on support for redistribution.

I want to highlight that I do not conceive of the cognitive process behind people's ultimate choice to be based on perfect information about the actual effects of governmental redistribution on the post-tax distribution of income. Individuals often lack a precise sense of whether they are net contributors or net recipients. Depending on the context and certain aspects being emphasised they might think of themselves as either one or the other. This amount of uncertainty allows for the use of heuristics and not strictly rational calculations in the formation of one's redistribution preferences. Beliefs about one's actual and deserved position in the income distribution and emotional/psychological responses to the presence of socio-cultural diversity therefore become signposts that can subtly veer people's preferred tax rate away from their material interest. In the end, when asked if they support more or less redistribution by the government, the utility they are seeking to maximise is the result of a complex mix of considerations, where they quite naturally 'hold certain things constant', weighing some more than others depending on the situation. Cramer (2016, 7) summarises this conception as follows:

People *are* taking economics into account. But these considerations are not raw objective facts. Instead, they are perceptions of who is getting what and who deserves it, and these notions are affected by perceptions of cultural and lifestyle differences. That is, in a politics of resentment, people intertwine economic considerations with social and cultural considerations in the interpretations of the world they make with one another.

The formalised approach I employ in this thesis is informed by this quite complex conceptualisation of people's subjective perception of their world. Nonetheless, I attempt to systematise *how* "people intertwine economic considerations with social and cultural considerations" Cramer (2016, 7), all while being aware of the high degree of abstraction

of social and psychological dynamics this entails. I derive the following hypotheses from the above:

Hypothesis 1 (Paying-for-Resentment Mechanism)

Support for redistribution declines when individuals perceive their relative rank and position in the income distribution to be under threat from below.

Hypothesis 2 (Income Effect)

The salience of this threat increases with lower income.

Hypothesis 3 (Immigration Effect)

The salience of this threat increases when the competitors are noticeably different, i.e. in a context of higher immigration.

Hypothesis 4 (Competition Effect)

The salience of this threat increases when economic competition is tighter, i.e. in a context of a compression in the bottom of the income distribution.

1.3 Empirical Approach & Findings

I do not profess nor aim to find the one mechanism which drives changes in preferences over redistribution across all contexts and for all people. In many ways, this is an impossible aim. When making micro-founded analyses of the aggregate preferences and attitudes of individual citizen, we as researchers invariably run into the issue that, to state the obvious, humans and human communities are quite complex. There are many interconnected strings to pull on to understand what people want, say and do. Accordingly, the theoretical intuitions developed here do not claim to untangle the whole knot, but to isolate one thread. One faces a similar challenge when trying to untangle things empirically. The breadth of the already existing literature on determinants of social policy preferences in general, and redistributive preferences specifically, is evidence for the fact that there are many different and often highly interdependent factors feeding into people's calculations. This poses a significant challenge to isolating the causal effect of the independent variables of interest, while at the same time trying to explain variation across different contexts. I therefore adopt a two-pronged empirical approach,

whereby I focus on descriptive inference in one analysis and on causal inference in another.

In the descriptive part of the thesis, I use survey data from the ESS and the ISSP spanning 20 years and 25 European countries. Due to the nature of this observational data, I cannot directly test whether the results are driven by the paying-for-resentment mechanism (H1). However, if such positional competition is a relevant driving factor for people's preferred level of income redistribution, one should observe lower support for redistribution where the competitors are more socio-culturally different (H3) and the competition is fiercer (H4). Moreover, this should result in systematically lower levels of support mostly among the poor (H2). I operationalise how different the competitors are as the change in the share of foreign-born population over the four years leading up to, and inclusive of, the survey year. 'Fiercer' (or tighter) competition is operationalised as the share of pre-tax income received by the bottom 50%. Individuals' position in the income distribution is measured by decile rank based on their household income equivalised by household size. I then explore the interactive patterns between these three variables with multilevel models with varying intercepts by country and year.

The findings suggest that increases in the share of foreign-born population are associated with lower support for redistribution, but only for the lowest five deciles of the income distribution. Moreover, while the interaction between the share of pre-tax income of the bottom 50% and income suggests that the rich are more supportive of redistribution when the poor have less, this pattern disappears in a context of high immigration. Correspondingly, the conditional negative effect of immigration on support for redistribution for the poor is only visible when the share of pre-tax income of the bottom 50% is lower, i.e. when the poor have less. These findings are in line with the empirical implications of hypotheses 2, 3 and 4. As stated above, I cannot directly test whether these are driven by the poor experiencing feelings of status threat under increased competition when immigration and inequality are high. Nonetheless, the results from the three-way interaction are coherent with the implications of the mechanism.

I try to uncover the mechanism more directly in the experimental part of the thesis. I present the design and results of a vignette survey experiment fielded in May 2018 with YouGov on a representative sample of the UK population. The 1,442 respondents

were randomly split into four groups. The first group, serving as the control group, was not shown any vignette before being asked to what extent they supported government measures to redistribute income. The second group was told, based on their self-reported gross household income, how much people poorer than them earn on average, before and after redistribution, and which percentile they belong to. The aim of this was to give respondents a sense of the competition they face from below. The third group was shown a two-sentence statement providing some simple figures illustrating the increase in immigration over the last couple of years. The fourth group, the main treatment group, was shown both the immigration vignette and the income position vignette. I produce average treatment effect estimates and conditional average treatment effects by income via regression, matching and causal random forests.

The results yield a statistically and substantively significant negative average treatment effect of the combined vignettes for the main treatment group. This is a finding that is robust to different specifications. Conversely, neither group that was exposed to only one of the vignettes exhibited significantly different support for redistribution from the control group. The magnitude of the average treatment effect for group four is larger than the sum of those for groups two and three. Moreover, the lower support in group four appears to be driven in part by a particularly large average treatment effect for the lowest income class. These findings can speak to the pertinence of hypotheses 1 and 3 in a way that the observational evidence cannot. Evidently, if informed about their rank and position in the income distribution relative to those poorer and how redistribution would narrow that gap, respondents became, on average, less willing to support income redistribution, but only when combined with information about the increased inflow of immigrants over the last decades. The experiment also provides suggestive evidence for a non-linear effect across income, and specifically a stronger negative effect for the lowest income category – in line with hypothesis 2. Hypothesis 4 cannot be tested with this experiment as it did not, by design, include variation in the shape of the income distribution that respondents were part of. It is worth pointing out that this ‘black-box’ approach to causality¹⁷ does not really make it possible to test whether the effect of the ‘threat from below’ works by triggering feelings of resentful

¹⁷Whereby an input element is manipulated by the researcher and its causal effect is measured by differences in an outcome variable of interest without specific manipulation checks or mediation analysis.

competitiveness that then depress support for redistribution.

Ultimately, both empirical approaches have their weaknesses, which I discuss in the conclusion of each chapter. Some of these weaknesses can be partly offset by the combination of the two. The observational evidence can provide a cross-context, descriptive perspective on the patterns of support for redistribution depending on income, immigration and inequality. The survey experiment makes it possible to isolate the causal effect of priming respondents on the increase of immigration combined with information about their relative position in the income distribution. Together, these findings provide some support for the theoretical argument, but also open up avenues for more research into the precise mechanisms that are at play here.

1.4 Outline of the Thesis

This thesis is structured as follows. In Chapter 2, I review the large body of literature dedicated to identifying the determinants of individual-level preferences over redistribution. Specifically, I emphasise which material and social factors have been found to be correlated with redistributive preferences and discuss how previous research has so far approached the interaction between these two dimensions. In Chapter 3, I detail my theoretical framework and formal model. In Chapter 4, I present observational evidence for my argument based on survey data from European countries between 2000 and 2019. In Chapter 5, I present the design and results of the survey experiment conducted in 2018 in the UK. I conclude in Chapter 6.

INTELLECTUAL CONTEXT | 2

2.1 Introduction

In the following, I discuss the literature dedicated to understanding the determinants of support for the welfare state, and more specifically redistribution of incomes from rich to poor. There is a strong consensus that the welfare state is sustained both by the vested material interests citizens have in it and some kind of social ‘glue’. Conversely, this means that the political sustainability of the welfare state would be threatened by the hollowing out of either pillar. While the first appears easier to define as the net gain for each individual, it is not always clear what the ‘sticky’ part of the second is. In broad terms, one of the main ingredients is seen to be (a sense of) ‘solidarity’ within a community of fate.¹ However, it is not always easily identifiable what the motivations behind solidaristic behaviour (or lack thereof) are. Therefore, qualifying the kind of social preferences that mainly constitute the above mentioned social ‘glue’ is an important feature of this research agenda. Furthermore, while there is little debate about the fact that both material *and* social preferences matter, there are more differences of opinion around their relative importance and whether they act in an additive and/or interactive way.

The first part of this literature review therefore summarises what is known about the effect of material circumstances on redistribution preferences. The second part focuses on the social components of welfare state support. The third section describes how

¹From a slightly different perspective, Levi (1990) speaks of the “quasi-voluntary” compliance sustaining the ‘social contract’ between the state and its citizens – a combination of self-interested and ideological compliance, where the strength and survival is strongly determined by its capacity to create such an ideology as to convince its citizens of the legitimacy of state actions.

these two components may interact and influence each other. Tying all of these back to the context of increased immigration to Western advanced capitalist democracies,² focussing primarily on either one of these determinants of individual preferences leads to (sometimes only subtly) different empirical implications.

2.2 Material self-interest

Most people care first about their own material well-being when forming opinions about the right level of redistribution. In the context of redistribution, material self-interest refers to the post-taxes-and-transfers income, in other words: disposable (household) income of individuals. This can be further distinguished into, first, disposable income in the present and, second, the expected level and volatility of disposable income (risk in the labour market) in the future, reflecting the two coins of modern welfare states: redistribution and insurance. However, in practice, the distinction is probably less clear-cut in individuals' preference formation than in the theoretical literature, as most social programmes involve both some redistribution from rich to poor and some cushioning against the risk of loss of income (c.f. Esarey et al., 2012, p.2), and being poor(er) in the present is often bundled with exposure to the risk of low income in the future (Barth et al., 2015). Essentially, the intuition is, depending on whether the (expected) net pay-off under the bottom line is positive (or negative), people will support more redistribution (or less). In choosing their optimal tax rate, individuals ask themselves "Will I benefit?" (Cavaillé and Trump, 2015, 148), and, in this reading, they do not care about the identity of the others.

The starting point for most models of redistribution preferences is undoubtedly the one from Meltzer and Richard (1981), which built on Romer (1975). Their model assumes a flat tax on all incomes and the same lump-sum transfer to everyone. The implication of their model is that all those richer than mean income have a preferred tax rate of 0%; those whose individual productivity is so low as to not make it worth it for them to work prefer a tax rate of 100%; and those in between have a linearly decreasing preferred tax rate, with respect to their income. Other approaches have made the same point by adding a dead-weight to taxation, which also means that the preferred tax rate

²Especially from poorer and culturally less similar countries.

decreases progressively with growing income (Przeworski and Yebra, 2006). Empirically, it has been found that individual or household income is often a pretty good predictor for redistribution preferences across different developed countries over time (Guillaud, 2013). Therefore, redistributive welfare spending can be understood as an “inferior good” (Barth et al., 2015, 566).³⁴

Expanding in this, other contributions incorporate the risk of unemployment. Iversen and Soskice (2001) argue that workers who take the risk to invest into (industry) specific skills face a lower change of re-employment, if laid-off, than those with general skills and therefore will ask for more social protection. In a similar vein, Moene and Wallerstein (2001, 2003) postulate that people are both motivated by unemployment insurance and redistributive concerns in their social policy preferences, and that these do not always have the same directionality. In short, if benefits were solely targeted to the unemployed, the employed with lower wages would be less supportive of the welfare state, as the immediacy of material circumstances takes over. Conversely, the sharper the fall between income and no income, the stronger the support for social intervention. Implicitly, they argue that support for unemployment insurance increases with income, while support for redistribution decreases with income (Moene and Wallerstein, 2001, p.864).⁵ Barth et al. (2015, 565) argue that there is a difference to make between variation between income categories and within categories. Each income class represents a set of social conditions (which they take to include risk) that are associated with a baseline support for redistribution, that decreases for each step up in income class. Within each category, those who are (or become) richer will lose more in the event of income loss and therefore support increases with income *within* those broader categories (Barth et al., 2015, 566).

Empirically, the effect of risk of unemployment on social preferences has been well

³⁴As opposed to a normal good, demand for an inferior good decreases with income.

⁴Of course, these models clearly make abstraction of the complexity of welfare state designs and the path dependent ‘feedback loop’ between social policy preferences and social policies (Gingrich and Ansell, 2012)

⁵The main point they make is that the relative importance of income vs. risk depends obviously on level of income and risk exposure but also on the institutional design of welfare states, more specifically the targeting of benefits (for a similar argument see Gingrich and Ansell (2012) or—on progressivity—Beramendi and Rehm (2016)). However, the focus of this literature review and subsequent theoretical argument is on individuals and their relationship to the others they share a common pool with. Therefore, also considering the moderating effect of institutional design (*how* things are distributed) both on material self-interest (*what* I get) and other-regarding preferences (*who* I share it with) would be—at this point—to complex.

documented (Cusack et al., 2006; Rehm, 2009). However, it does not always correlate perfectly with present income. Through the increasing segmentation of labour markets and growing labour market insider-outsider divisions (Rueda, 2007; Schwander and Häusermann, 2013; Alt and Iversen, 2017), risk exposure to job-loss has been shown to vary across skills, industries and occupations (Iversen and Soskice, 2001; Kitschelt and Rehm, 2006; Rehm, 2009, 2011; Rehm et al., 2012).

A further strand of the literature focusses more generally on life-cycle income, rather than just the risk of unemployment. For instance, in their work, Bénabou and Ok (1998, 2001) argue that people with expectations of upwards social mobility (and low risk aversion) will have lower support for redistribution. This argument, also called POUM-hypothesis, appears well supported in the US, but found less evidence in Western Europe (Cojocaru, 2014). Alesina and La Ferrara (2005) measure ‘objective’ life-cycle prospects of different segments of society and, again in the US, find positive prospects compared to present income to be related to lower demand for redistribution and vice versa (see also: Alesina and Giuliano, 2011). Similarly, Rueda et al. (2014) find that expected income may have a much stronger impact on redistribution preferences than current income in Western Europe.

In the end, all these explanations for the level of individual support for redistribution deal with the aforementioned question “Will I benefit?”. And while risk and income may not fully map onto each other, they are still very much correlated (c.f. Barth et al., 2015) and it seems intuitive that their combination creates a scale of economic vulnerability along which people in society are ranked. Accordingly, high income households are generally the least insecure (Rehm et al., 2012, 388). Beyond their present wage, the accumulation of income and other sources of wealth mean that they can fall back on other types of ‘private insurance’ such as housing or financial assets, for example (Ansell, 2014).

If people care only about what they get out of the welfare system, changes in the impact of immigration on individual support for redistribution will purely be a function of its net effect on people’s disposable income and their relative position in the income distribution. Assuming a mean immigrant lower than the domestic mean income (and assuming a simple Meltzer and Richard redistribution model⁶), more domestic citizens

⁶And ignoring as well the more long-term, often positive, economic effects of immigration into the ageing Western democracies.

would become net contributors. Hence, support for redistribution among those citizens would decrease, leading to overall less support for immigration. Taking a slightly more sophisticated understanding of material benefits to also include the level and volatility of future income, the influx of immigrants could actually increase support for redistribution: for those people have skills and occupations that match those of the incoming immigrants, this means more competition for the same jobs and therefore a higher risk of unemployment against which they may want to insure against (Brady and Finnigan, 2014). All in all, considering only material self-interest implies that those people who change their support are those whose material pay-outs increase or decrease in terms of the benefits they receive or their income: a decrease in (expected) income would lead to more support for redistribution; and a decrease in expected benefits would mean less support. If these changes to the balance sheet were due to a change in the ‘domestic’ income distribution, the same outcome would be expected.

Yet, this places strong assumptions on people’s knowledge about the complex ways in which immigration will impact the country’s economy, the government’s tax revenue and expenditure and their personal situation in the long run. Therefore, what will matter is the *perception* of personal gain or loss from redistribution (c.f. Cansunar, 2021). Talking about perceptions, however, risks opening quite the Pandora’s box. Perceptions – or what is (subconsciously) chosen to be perceived – could be affected by a number of things. Social preferences – or, in other words, how people feel about others in the common pool – are a crucial puzzle piece in this respect.

2.3 Social preferences

The welfare state does not operate in a ‘societal vacuum’, where differences between individuals are restricted solely to economic factors such as income and occupational risk. The academic literature has therefore sought to establish whether it matters to support for redistribution when people ask themselves “who are the others who will benefit and how do I feel about them?” (Cavaillé and Trump, 2015, 6). Broadly speaking, it seems that people care about the structure and composition of the common pool the welfare state is based on. Putting it in a slightly stylised fashion, the basic ideas is that a) positive feelings would make people want to invest (more) in that

common pool, even though that incurs costs for them. In simpler terms: they want to give to others. And b) more negative feelings about said common pool would lead people to want to invest less or even exit the common pool, even though they profit from it materially, by internalising the incurring costs. Again in simpler terms: they want to take away from others. In a way, the underlying theme to all the approaches described above, namely that what individuals consider a *fair* allocation of material outcomes inform people’s willingness to support social welfare programmes beyond their own material self-interest (c.f. Cavaillé, 2015). And they are willing to bear the costs to re-establish a balance of what appears ‘just’ to them.

First, what matters is the type of social preference – *what feelings* the individual has about the allocation to others. In more formal terms, is the individual’s utility function increasing with the utility of others (altruism), decreasing (spitefulness), or increasing when they are too poor and decreasing when they are too rich (inequity aversion). Altruism models quite straightforwardly imply that people care both about their own self interest and that of others. The relative weight of each component then determines how much they care. Assuming a basic level of altruism across society, individual support for redistribution would exceed one’s material self interest in order to help raise the pay-off of the poor (for instance: Rueda, 2017; Dimick et al., 2017, 2018). This is often also termed inequality aversion (Fehr and Schmidt, 2006, 638). Conversely, spitefulness is the opposite where people’s utility is decreasing with other’s pay-offs. Fehr and Schmidt (1999) argue that people are inequity averse and therefore do not like when people get more or less than commonly accepted upper and lower thresholds of fairness (for a similar idea see: Bolton and Ockenfels, 2000). In this case, people want to redistribute to help the poor and to limit the rich.

Second, social preferences models can be extended by considering *what actions* the others take – do they deserve to be helped or not. Alesina and Angeletos (2005) expect the strength of demand for social fairness and therefore support for redistribution to decrease when the income distribution (and inequality) is seen more as the product of effort (or lack thereof) rather than pure (bad) luck.⁷ (Perceived) effort by the poor could therefore increase individuals’ willingness to help them. Furthermore, willingness to help

⁷They go on and argue that people in more unequal societies tend to attribute outcomes less to luck, with the US as a paradigmatic example. This makes it unclear then if beliefs about luck and merit are a reason for, or a consequence, of unequal societies.

or to harm could also depend on reciprocity. In experimental settings, people have been found to be more likely to act altruistically if the other player behaved altruistically before. Conversely, if the other player ‘misbehaved’ they would become spiteful and punish them (for example: Cox et al., 2007). People may also have expectations about how others would behave and hope that if they act altruistically, the other would reciprocate.

In the context of welfare state support, willingness to redistribute could be explained by expectations about the reciprocity of the poor, that they would be more productive and be able to contribute more to the common pool if helped. This would mean that immigrants showing willingness to contribute and hard work could lead to altruistic feelings being extended to them. Hainmueller et al. (2015, 3, see also: Hainmueller and Hopkins 2014) argue that people have “sociotropic considerations about the effects of immigration on the country as a whole” which conditions their support for immigration. Transposing this idea to redistribution, lower support could be caused by immigrants’ lack of ‘history’ of reciprocity due to their recent arrival and uncertainty about their willingness or capability to contribute to the country’s performance. Similarly, by conducting a series of experiments in Uganda, Habyarimana et al. (2009) argue that the reason why heterogeneous social entities are less effective at providing collective goods is not because of out-group prejudice, but due to a set of reciprocity norms that are shared within ethnic communities. And yet, what would explain why these reciprocity norms are shared with one group and not others? If it is not related to identity, shouldn’t such norms develop over time to include others if reciprocity and effort is observed (perceived)? Outside of controlled experimental environments, it appears unlikely that perceived effort accurately maps onto the actual effort, a difference that could be explained by prejudice against the out-group. There are persistent negative beliefs about immigrants’ deservingness (c.f. Van Oorschot, 2006) which could not be explained by a supposed lack of effort. There seems to be a prevalent assumption that native-born are by default more deserving than the (culturally dissimilar) immigrant newcomer.

Third, a further extension is therefore to take into account *who* the others are. In-group favouritism could be explained by an inherent mistrust and dislike of the ‘other’ (c.f. Tajfel, 1982), a dimension that can outweigh material self-interest (Lee et al., 2006). Consequently, the importance of altruism may vary depending on the individual’s

social “reference point” (Alesina and Angeletos, 2005, 965) and on the composition of the rest of society. For instance, altruism may extend to a specific in-group “only if they have a sense of belonging or shared identity with [the poor], whether the motive is religious, ethnic, or racial” (Alt and Iversen, 2017, 23). If individuals care only about members of their own group, increasing diversity and cultural distance (especially among the poor) reduces the relative share of the population they wish to see do well, which in turn reduces the optimal tax rate. There is a large body of literature that has theorised and documented the effects of out-group bias onto support for the welfare state. The essence of many arguments is that the ‘inside-group’ majority turns against the welfare state in the presence of ethnic and cultural heterogeneity because they do not want members of the outside group to receive welfare provisions. In some way, they perceive the outsider to illegitimately profit from redistribution. One set of reasons for this “distaste” (c.f. Luttmer, 2001) for redistribution to culturally dissimilar people has been attributed to nationalist (Shayo, 2009), xenophobic (Finseraas, 2008, 2012; Eger, 2010; Eger and Breznau, 2017), even racist (Gilens, 1996; Alesina and Glaeser, 2004; Lee et al., 2006; Harrell et al., 2016; Schmidt and Spies, 2014), attitudes. From this point of view, immigrants do not deserve support in terms of redistribution, simply because they are different and not part of the ‘true’ nation.

Clearly, there is a degree to which members of the native-born majority react (often negatively) towards members of out-groups, and in particular immigrants, in the context of support for redistribution. But through which of these mechanisms does this out-group bias translate into changes in demand for redistribution? Summarising this purely as dislike of the other, due to immutable tribal reflexes which then creates lower support for redistribution across the board at all levels of income, is missing part of the picture. Assuming that everyone has some level of an inherent out-group bias, in the same way that everyone may have some level of altruism, it is important to ask what makes it salient – or not. People are probably subject to different social preferences at the same time, that may be ‘activated’ under different circumstances. Most importantly, the literature so far is not very clear on how individual material circumstances interact with social preferences.

2.4 Material self interest $\pm/\times$ social preferences

How are material self interest and social preferences related to each other? Instead of being seen as just additive effects, when does one aspect trump the other, or when do they potentially magnify each other? Cavaillé and Trump (2015) argue that the two dimensions are theoretically distinct and show evidence that attitudes are also empirically distinct and have developed differently over time in the UK and Germany. The welfare state still seems to enjoy widespread popularity (Pierson, 2001, 410) for what people *get* out of it. At the same time, the universality of welfare states seem to be put into question, with many supporting restricting access and coverage. The welfare state loses popularity because of who it redistributes to (Cavaillé and Trump, 2015). This can be taken to explain why welfare chauvinism – a generous welfare state but exclusion of members of out-groups (non-citizens) from it – has become increasingly popular (Mewes and Mau, 2012, 2013; Van der Waal et al., 2013) and has become a lucrative policy platform for many radical right, nationalist parties (Schmidt and Spies, 2014; Cavaillé, 2016). This, however, implies that voters have the possibility to choose their preferred tax rate *and* the level of access to the welfare state at the same time. But this is rarely the case and often people are faced with “circumstances in which changing the funding level is politically easier than altering a program’s design” (Moene and Wallerstein, 2001, 863). While the politics of structural change of the welfare state are a fascinating subject, this dissertation takes another perspective and seeks to answer the question: what is the effect of immigration on people’s preferred tax rate *given* a certain level of rights and access for immigrants?

Even though the mechanisms behind the two attitudinal dimensions operate differently and people, if the extensiveness of rights, i.e. the ‘who’ in “redistribution to”, is exogenously set, there is ultimately only one optimal tax rate each individual can choose based on the above described utility function: social expenditure and taxation “are two sides of the same coin, inextricably linked” (Pierson, 2001, 424). When forming opinions about the level of welfare transfers, which are then translated into survey answers or into votes, it is hardly explicit which dimension the question posed aims at. Therefore, both pecuniary and other-regarding motivations come together to form one

single response.⁸ What is interesting now, is *how* the two dimensions could interact in the presence of increased immigration and ethnic heterogeneity to form one single result when people are asked about their preferred level of taxation.

The idea that these two dimensions are related to and can interact with each other under circumstances to affect people’s utilities is not new. Dimick et al. (2017) and Rueda (2017) for instance argue that only the rich can ‘afford’ altruism. In the presence of diversity, this would suggest that only those on the right hand side of the income distribution will be affected by the identity of the poor (see also: Alt and Iversen, 2017; Höchtel et al., 2012). In short, if the rich feel a sense of belonging and solidarity with the poor in their country, an altruism bonus makes their preferred tax rate higher than what would be expected according to their material situation. In this case, the material side determines whether the non-material side will affect the utility function.

Other studies have – maybe implicitly – focused on the opposite link, namely how the non-material side affects how an individual feels about her own material situation. Alesina and Angeletos (2005) argue that if the pre-tax income distribution is perceived to be the result of effort and hard work⁹ as opposed to luck, support for redistribution will be lower, and vice-versa. Shayo (2009) presents a model in which support for redistribution among the poor will depend on whether they identify with the nation or with their social class. In the former case, feelings of being part of a ‘greater whole’ mean that one feels less as being part of the working class – especially in the presence of ethnic heterogeneity – and therefore lead to lower support for redistribution. In the field of economics, an experiment presented by Card et al. (2012) found that, when presented with information about their relative salary position compared to their peers, those below the median exhibited significantly lower levels of job satisfaction and an increased likelihood of looking for a new job. Based on these, a further extension to the social preference models discussed above can be added: whether the utility of others enters the individual’s calculation in absolute or in relative terms. Such positional arguments generally focus on feelings of competition, relative deprivation and satisfaction (Yitzhaki, 1979).

⁸Obviously, this is true in situations where the question about redistribution does not in fact hint itself towards one or the other dimension. Rather than seeking to uncover and analyse how people respond once one or the other dimension is made more salient, the idea here is first to see how the two dimensions interact without external nudging. This would then be the next step.

⁹Meaning that their material situation is the result of a fair process.

Within the experimental behavioural economics literature, more attention has been paid to the interconnection between other-regarding preferences and decision making under risk of income loss, exemplifying how the social context may affect material calculations (e.g. Boles and Messick, 1995; Krawczyk and Le Lec, 2010; Bolton et al., 2014). One of the themes of this field is the role of social reference points in eliciting more risk-seeking behaviour, “if the aspiration level can be met or surpassed by assuming greater risks” (Trautmann and Vieider, 2011, 8). There is some evidence that people “are apparently willing to risk earning less in order to have the chance to earn more than their peer” (Linde and Sonnemans, 2011, 8; see also: Bault et al., 2008). The importance of reference points in general is further illustrated by one notable experiment by Shea (1995). It showed that consumers might not adapt their present consumption v. saving decision according to expected utility when presented with “bad news” (a cut) about their income in the next period (Camerer et al., 2004, 153). In an assessment of the state of the art, Camerer et al. (2004) discusses the explanation for this surprising empirical finding. These suggest that the peoples’ consumption is “sticky downwards” (2004, 153) because they have a certain reference point for their consumption and therefore strongly dislike having to cut back. Therefore, “they are willing to gamble that next year’s wages might not be so low; thus, they would rather take a gamble in which they either consume far below their reference point or consume right at it than accept consumption that is modestly below the reference point” (Camerer et al., 2004, 153; see also Kőszegi and Rabin 2006, 2007).

Kuziemko et al. (2014) present interesting findings for the phenomenon called “last place aversion”. Contrary to classical models of risk aversion, they find that those at the bottom of the income distribution are significantly more willing to take a gamble that would allow them to move up one rank as opposed to a secure pay-off. Furthermore, when given a monetary amount to distribute, individuals in second-to last position were much more likely to give the pay-off to the above rank than the one below (Kuziemko et al., 2014, 113-133). They also test this argument in the context of the welfare state and find that those directly above the minimum wage are significantly less supportive of an increase of it than expected, because they “would no longer have a group of worse-off workers from whom they could readily distinguish themselves” (Kuziemko et al., 2014, 107).

Corneo and Grüner (2000, 2002) emphasise the role of social competition and the urge to differentiate oneself from the social group just below as well as to emulate the one above. They argue that this could explain low support for redistribution even for those who technically benefit from it, depending on the structure and distance between the social groups in a country. More recently, Kim (2019) proposed a model of positional concerns that could explain the social conservatism of the poor. It is within the latter strand of the literature that my contribution is situated, adapting an argument about relative income position to a context with immigration.

2.5 Conclusion

If people followed only material self-interest, their support for redistribution would only change depending on the effect of immigration on their pay-offs, either on their personal income, or the benefit(s) they receive. Adding to this social preferences in an *additive* way would predict that support for redistribution would just be uniformly higher or lower by the same amount than individual self interest across the income distribution. However, this approach cannot account for different reactions by different income groups. Many explanations linking immigration to lower support for the welfare state base their argument on “the salience of subjective group boundaries” (Eger and Breznau, 2017, 444) which leads to lower solidarity. There is evidence for correlation between the two, however it is not unambiguous. Beyond methodological challenges to clear causal inference, attention has turned to several scope conditions (institutions, economics, politics...) that may moderate that relationship. If the link between diversity and lower support for the welfare state is not automatic, this means that out-group bias leading to declining national solidarity, which is understood to be the core of modern welfare states, is not a sufficient explanation in and of itself. And if scope conditions matter, this means that there is variance in the way ‘reflex-like’ out-group bias interacts with individuals’ personal economic environments to produce different attitudinal patterns. There is a need for a more in-depth theorising about how immigration and the ensuing increased diversity affects individuals such that de-funding the welfare state appears to be the solution.

Ultimately, it is probable that everyone has the potential for different social prefer-

ences at the same time (not all of them relevant to welfare state), that get activated given the situation the people are in. Therefore, an interactive relationship between material self interest and social preferences is the most promising avenue to understand support for redistribution in the context of immigration. This is an approach that has so far been under-developed, and therefore provides the starting point for my theoretical contribution. By doing so, I seek to advance the understanding of *why* citizens react negatively or positively to each other, a crucial element for assessing the sustainability of welfare states.

3.1 Introduction

As the discussion in the previous chapter has illustrated, the literature on the subject has fallen short on the following accounts. First, the interconnection between material circumstances and social preferences – and more specifically the importance of the social context in conditioning individuals’ reactions to vulnerable economic situations – has been largely absent from discussions on support for the welfare state. Second, and relatedly, explanations of the impact of immigration on redistribution preferences have been unclear about the interconnection between material circumstances and other-regarding (social) preferences, often treating reactions to immigration as rooted in *either* socio-cultural or economic fears. And, finally, few approaches so far have explicitly differentiated between a notion of relative, comparative justice and normative justice for motivating other-regarding preferences and incorporated the former.

In response to these shortcomings, I propose a mechanism where social fears mediate economic fears, which offers a justification for low income individuals’ lower support for redistributive measures than is in their material interest. I term this mechanism *paying for resentment*. The choice of the word “resentment” here captures the intrinsic status-oriented interpretation of this type of inequality (Feather and Nairin, 2005) and the “[b]itter indignation at having been treated unfairly”¹ it may cause. The “paying” element reflects that in order to correct this situation, people are ready to forego some *absolute* material benefits in order to preserve (and possibly improve) their advantageous

¹Source: <https://www.lexico.com/definition/resentment>. Last accessed on 10/05/2021.

relative pay-off.

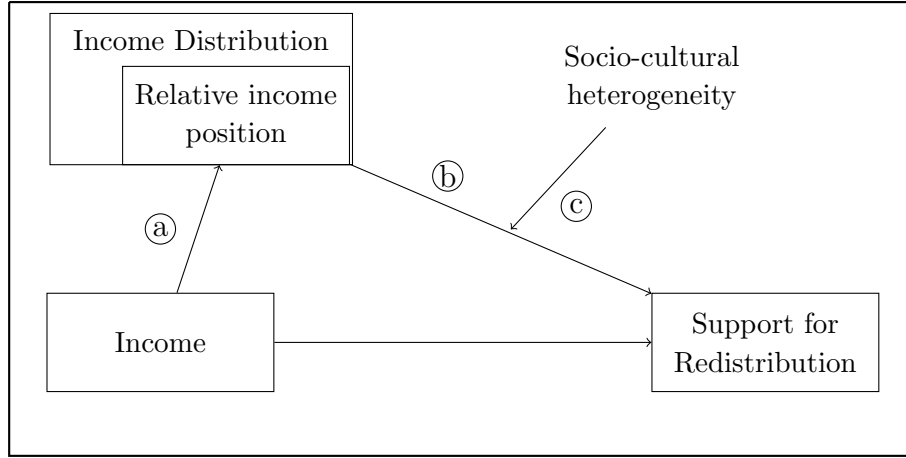


Figure 3.1: Mechanism

I summarise the mechanism in Figure 3.1. This diagram encapsulates the idea that an individual's income affects their support for the welfare state through two channels. One, direct, is represented by the solid line and represents the 'standard' material self-interest mechanism. The other one is indirect and the subject of this thesis.

The argument rests on the supposition that, in addition to the absolute utility derived from their disposable income, people derive social value from the *relative* consumption position it confers them. It distinguishes them from those less well-off and leads them to endogenously form beliefs about those income differences being 'justified'. Importantly, I deliberately focus here on downwards comparisons, as measured by percentile and distance to the poorer. This corresponds to arrow (a) in Figure 3.1. Another, related assumption is that the utility drawn from both the absolute income and relative income position has decreasing marginal returns. In less formal terms, this means that those who have less of something tend to value each additional unit of that 'something' more. Hence, as with income itself, relative position matters more to the poor than the rich, as they have less of it to begin with.

Given this assumption, it follows that this could have implications for levels of support for redistribution, as shown by arrow (b). Redistributing from rich to poor compresses the income distribution and reduces its skew and kurtosis. Therefore, utility gains with respect to absolute disposable income may be counterweighed by utility losses in the relative position, thereby depressing support for redistribution. Because of decreasing marginal returns and since the rich incur utility losses through both channels

with more redistribution, this will have more traction with the poor. I justify the intuitions behind arrows (a) and (b) in section 3.2.1.

The final tenet of the argument is that how individuals value relative income position – i.e. how important the positional “externality” (Kim, 2019, p.29) is – and therefore how much it will play into support for redistribution depends also on socio-cultural heterogeneity. This corresponds to arrow (c). The hypothesised implication is that the relative income position becomes more salient in a context of increased immigration, leading to a decrease in support for redistribution. This is because other dimensions other than relative consumption levels, such as ethno-cultural differences, contribute to perceptions of social status. If, as I assume, relative income differences act as signals for social value to individuals, (xenophobic) beliefs about the ‘right’ socio-economic hierarchy based on cultural differences between a ‘domestic’ and immigrant population will intensify the importance of maintaining these relative income differences. This is the topic of section 3.2.2.

I present a formalised version of the argument in section 3.3.

3.2 The Argument

3.2.1 Income, Positional Competition and Redistribution

Numerous studies in economics, social psychology and even neuroscience have provided ample evidence for the fact that people care about and are deeply affected by the inequality that surrounds them (Jetten and Peters, 2019). Clark and D’Ambrosio (2015) differentiate between two types of individual attitudes to inequality: a normative, “disinterested evaluation of income inequality” (p.1149) and a much more self-interested reaction to inequality, “with the additional assumption that individuals care not only about how much income they receive but also about how much they receive compared to others” (p.1149). Hence, the effect of inequality on utility could run through both mechanisms.

In a review of the literature on relative deprivation, Rose (2006) discusses evidence that indicates that individuals’ views on what he summarises as micro justice (i.e. self-centred, comparative inequality) and macro justice (i.e. overall inequality) are not the same, and may even be opposed. People may perceive overall inequality as too

high, but not believe that their own or other’s position is unjust, and vice-versa. In more formal terms, inequality aversion may not be the same when it relates to overall society than when it comes to an “individual’s belief about whether what s/he gets is just” (Rose, 2006, 9).

This distinction is important, firstly because these two types of inequality aversion are not necessarily correlated and their salience may depend on individual income. While (conditional) altruistic feelings may be more relevant for the rich (c.f. Alt and Iversen, 2017; Dimick et al., 2017), I argue below that comparative inequality aversion matters more to those in the lower part of the income distribution. Secondly, reactions to feeling personally unjustly treated are arguably quite different in intensity from altruistic feelings towards a larger, rather ill-defined group of people. In a time where politics and feelings appear more intertwined than before, resentment could be a far more mobilising drive. As Ridgeway (2014, 2) put it:

When we think of inequality as merely a structural struggle for power and resources, we forget how much people care about their sense of being valued by others and the society to which they belong.

My argument is one about social comparisons, status competition and the feelings of resentment towards those challenging one’s position, which then depress support for redistribution. It starts with the assumption that individuals tend to make social comparisons and care about what they have compared to others.² They do so insofar as their relative position at the same time confirms and informs them about their social status – the relative amount of esteem and respect a person receives (Weber, 1921) – in society. And to gain outward recognition of that position, a clear demarcation from those below is crucial, leading people to perceive income differentials between them and people in the income classes below them as *justified*.

This is a self-reinforcing mechanism: from factual differences in economic resources, “people form status beliefs that the ‘type’ of people who have more resources [...] are ‘better’ than the ‘types’ with fewer resources” (Ridgeway, 2014, 3). These “cultural status beliefs about group differences regarding who is ‘better’” (Ridgeway, 2014, 1) then help further “justifying and legitimating the resource and power inequalities between

²Such attitudes are not easily classifiable as either self-interested or social preferences, but could rather be defined as self-interested social preferences.

[...] groups” (Ridgeway, 2014, 6). As such, income differentials act as a signal for a particular status within the social hierarchy, while at the same time further validating the legitimacy of that particular social ranking and the (im)permeability of group boundaries.³ From this, subjective beliefs develop about the relative position that one (and others) are ‘owed’.

At the same time, social comparisons fuel status competition, generating “competitive behavior to protect one’s superiority” (Festinger, 1954, 126 cited in: Garcia et al., 2013, 635). This means that people seek to maximise the distance to people ranked lower than them and minimise the distance to people ranked higher than them. Moreover, others that are (or are perceived to be) challenging the established social hierarchy and threatening the beholder’s social status will often be met with “hostile backlash” (Ridgeway, 2014, 7). In other words, it fuels resentment about their gains that are perceived as ‘undeserved’ (Feather and Sherman, 2002),⁴ because those gains challenge the established social hierarchy.

The question then is, which one would people tend to care about: upwards or downwards comparisons? The unsurprising answer is probably both (Clark and D’Ambrosio, 2015). However, and relevant to the present argument, the relative importance of either type of comparison may depend on one’s initial rank and hence from which direction the threat to one’s status is most likely to come. For instance, Garcia et al. (2006) and Garcia et al. (2013) present experimental evidence of intensified competition near a relevant standard, and most notably either close to the top ranking or close to the bottom ranking. It seems intuitive that individuals would gain more satisfaction from *having the chance of increasing* their rank if they are near the top of the distribution than lower down. Equally, it appears intuitive that individuals would have more dissatisfaction from *facing the threat of decreasing* their rank if they are closer to the bottom of the distribution than higher up. The last-place aversion effect described by Kuziemko et al. (2015) can be ascribed to a similar logic: even if one has a low income, people value being able to clearly distinguish themselves from a worse-off group, and fiercely compete to avoid being last.

Therefore, this thesis’ argument focusses on downward comparisons and competition

³On the psychological mechanisms of inequality justification see Blanchard and Eidelman (2019).

⁴See Zeigler-Hill and Shackelford (2018) for a review of dispositional envy and its relation to feelings of resentment.

to preserve one’s superior position. While upward comparisons may distract the rich from their ‘objective’ self-interest to support more redistribution (Cansunar, 2021), it is downward comparisons that could arguably distract the poor from their ‘objective’ self-interest to support *less* redistribution. Thereby, I argue that social comparisons against those below are more salient for attitudes towards redistribution for those lower down the income distribution.⁵

Essentially, the expectation here is that the effect and salience of social comparisons are likely to not be constant across the income distribution and most salient for the poor. As Cramer (2016, 9) describes it, “[a] politics of resentment arises from the way social identities, the emotion of resentment, and economic insecurity interact”. I therefore expect the marginal returns from maximising relative position to decrease as the rank in the income distribution increases. As the status struggle is a struggle for distinction from others, those with fewer people below them are the ones that have the most to lose in terms of relative status from a compression of the income distribution.

Analogously, it has been shown that relative position gains in importance with higher uncertainty about future prospects. For instance, Kőszegi and Rabin (2006, 1136) argue that “when there is uncertainty, a decision-maker’s preferences over consumption bundles will be influenced by her environment”. Bault et al. (2008) provide evidence showing that people judge the relative importance of gains and losses differently in private or social environments. This intuition is supported by findings in the behavioural economics literature that show that the evaluation of material prospects can be strongly affected by the social context. For instance, it appears that people become less risk-averse when choosing over lotteries in social environments compared to private settings (Bault et al., 2008). Furthermore, some experiments show that people often reject “positive but inequitable offers even though the alternative is no gain at all” (Loewenstein et al., 1989, 426). Following from the above, I expect that people lower down the income distribution will care more about their relative distance to those below them and will do so particularly if immigrants make up an increasing share of society. They are “willing to risk earning less in order to have the chance to earn more [than them]”

⁵This could also be likened to the so-called *N*-effect, which predicts that “in large-*N* environments, social comparison becomes less important, and competitive motivation diminishes” (Garcia and Tor, 2009, 872). The logic here is that, when the number of competitors increases, the signal given by social comparisons becomes diffuse and less informative about one’s position in society. This further justifies the intuition that competition would be stronger towards the top or bottom ends of a ranking, where there are less competitors fighting for getting the top or avoiding the bottom position.

(Linde and Sonnemans, 2011, 8). Therefore they will choose a *lower* tax rate than the one that maximizes their material self-interest.

This brings me to discuss more explicitly arrow (b) in the mechanism, illustrated in Figure 3.1 above. If it is assumed that people care about their relative income position, in particular relative to those poorer, redistribution becomes a threat to a social ranking perceived as ‘deserved’ by reducing income differences. The social value attached with a particular income decreases as income signals become more mixed and more overlap between social groups occurs. And if one’s status position and its clear demarcation is under threat, it can lead to resentment towards those other groups below who start overlapping with one’s own.

By compressing the income distribution, redistribution may encourage these feelings not because others with whom little affinity is shared get something in absolute terms, but because what those others pay in and receive reflects on the social value of one’s own net pay-offs and challenges one’s status. Even if an individual technically gains from redistribution in purely material terms, they may not want to pay into a system from which they get less than feels just compared to a benchmark set by relevant reference groups.

This is in line with arguments that say that “[p]eople put additional value on outcomes that help them to achieve their aspiration level, for instance a social comparison outcome” (Trautmann and Vieider, 2011, 8), which may distract them from their material self-interest. Resentment about distributional conflict and injustice (be it perceived or real) can lead people to feel *schadenfreude*⁶ (Feather and Sherman, 2002; Feather and Nairin, 2005) about “victories over people perceived as undeserving” (Cramer, 2016, 9). In this context, reducing the preferred tax rate pays for resentment by trading utility in terms of objective, material benefits for satisfaction about preserving a social ordering perceived as legitimate. From this reasoning I derive the following hypotheses:

Hypothesis 1 (Paying-for-Resentment Mechanism)

Support for redistribution declines when individuals perceive their relative rank and position in the income distribution to be under threat from below.

⁶A sense of pleasure about failure of others, in short utility.

Hypothesis 2 (Income Effect)

The salience of this threat increases with lower income.

3.2.2 The Role of Socio-Cultural Heterogeneity

Throughout the discussion above, some reference has been made to the role played by the social context, albeit without further specification. I argue that the positional competition should be fiercer in a context of salient cultural and identitary heterogeneity. If people care about preserving their position relative to those poorer, they especially care about preserving their advantageous position relative to those they perceive as particularly different from them.

It is well established that social status should be conceptualised as multi-dimensional and not only an expression of income and wealth. Indeed, “when control over resources in a social setting is correlated with a salient categorical difference (e.g., race), people quickly link the appearance of mastery in the situation that the resources create with the associated difference between types of people” (Ridgeway, 2014, 3). One of these central dimensions are ethno-cultural differences. In the US, the particularly salient cleavage has of course long been and continues to be race and its history of slavery (Pontusson, 2006, 322). Across many developed countries, including the US and Europe, immigration and the increased ethnic diversity that comes with it has emerged as a source for one of the core political and social schisms. That is not to say that the political, social and institutional processes around the US’s history of racism against African Americans are in any way the same than those around recent immigration (and vice versa). However, they are both linked to beliefs about social status hierarchy.

Gidron and Hall (2017) argue that contemporary support for populism is not explained either by cultural or economic factors separately, but rather how they intertwine to form subjective social status.⁷ And threats to social status are likely to make people particularly susceptible to hostility towards clearly identified out-groups (Gidron and Hall, 2017, 8). Immigrants represent such an easily identifiable out-group in this context: they have, to varying degrees, different customs and can easily be seen as not ‘belonging to us’. This leads to expectations that native-born populations ‘should be prioritised

⁷They define social status as ‘the level of social respect or esteem people believe is accorded [to] them within the social order’ (Gidron and Hall, 2017, 6)

over them'. Immigrants can be seen to have, by default, a less deserving position than native-born because being a more recent part in the national community, and social hierarchy should reflect that “generally recognized asymmetry in players’ claims or obligations” (Cox et al., 2007, 9).

This social gap between native-born and foreign-born may create expectations that the income distribution should mirror these social differences. And this, in turn, may foster resentment if these expectations are not met, which leads to lower demand for redistribution to correct for this. The fact that immigrants, the contrasting out-group *par excellence*, are aided by the state through redistribution affects the feelings people have about their own relative pay-offs. This then fuels status competition even more, and the importance of maximising relative income differences compared to absolute gains increases.

People in a more vulnerable economic situation which already challenges their social status may especially see immigrants as the reference group to distinguish oneself from. The poor may find in clear social boundaries along national and ethnic lines and the implicit hierarchy associated with them an alternative source of a sense of social dignity (see Lamont, 2000; Lamont and Molnár, 2002). Frustration about present and future economic insecurity paired with the presence of an out-group that is technically comparable in terms of economic situation could lead to shame about facing the danger of ending up at the same level as them, which turns into resentment. Therefore, immigrants can be seen as an important reference point against which native-born evaluate their relative position – i.e. ‘I might not be doing too well economically, but at least I am better off than immigrants who deserve less than me’ – and can be the subject of stark resentment if they are perceived to be faring too well compared to what is socially constructed as just. Consequently, they may revert to maximizing their utility by increasing advantageous inequality between them and immigrants by decreasing the compressive effect of the income distribution and thereby increasing their relative pre-redistribution income.

Cramer (2016) describes in her book the resentment present in rural areas of Wisconsin towards urban areas and public institutions that seem to not be working for them. In this context, where people believe they are not getting their fair share out of the welfare state, the consequence is not higher but lower demand for the welfare state.

While she does not directly consider the impact of race divisions, she acknowledges that this mechanism could apply in such a context as well. In her assessment, resentment grows out of the identification of an *other* group because of the *otherness* and the perception that, *compared to* that group, they are being treated unfairly. Resentment is closely linked to a strong “sense of distributive injustice” (Cramer, 2016, 12). This refers to the perception that a) one and one’s peers are not receiving their fair share; b) while others (in this scenario, immigrants) are undeservingly profiting from social benefits funded with one’s hard-earned tax dollars; and c) that is given to them by a state that ignores one’s needs (Cramer, 2016, 154-158). In this context and through the looking glass of this resentment towards other people within the same country, support for less redistribution and smaller government appears as a logical consequence (Cramer, 2016, 24).

To sum up, I argue that social comparisons are more important to individuals, status competition more fierce and therefore feelings of resentment heightened in a context where ethnic heterogeneity in the form of immigration is more salient. Such a context represents a situational trigger that can activate and strengthen the limiting effect of social comparisons on support for redistribution hypothesised in the previous section. This leads me to the following, third, hypothesis:

Hypothesis 3 (Immigration Effect)

The salience of this threat increases when the competitors are noticeably different, i.e. in a context of higher immigration.

3.2.3 The Role of the Income Distribution

Many have sought to understand the role of inequality and its relationship with public support for, as well as levels of, redistribution. Specifically, a lot of research (to cite but a few: Moene and Wallerstein, 2003; Kenworthy and Pontusson, 2005; Kenworthy and McCall, 2008; Jæger, 2013; Schmidt-Catran, 2016) has been dedicated to establishing whether, or explaining why, the association between inequality and welfare state generosity does not (always) follow the Meltzer and Richard standard expectation.⁸ A large number of such work relies on summative measures of inequality, such as the

⁸Their model predicts higher redistribution when inequality and the distance between median and mean income are higher.

Gini Index for instance, that are more or less sensitive to specific changes in the shape of the income distribution. However, among others but most prominently, Lupu and Pontusson (2011) argued that 50-10 and 90-50 interdecile ratios are theoretically more appropriate measures, as they capture the *skew* of the distribution and therefore the relative distance between the low, middle and high income groups. They argue that, depending on whether the middle class is economically closer to the poor or the rich, they will feel more social affinity towards and align their social policy preferences with the closer group.

It is not my aim to directly engage with the debate about the inequality-redistribution nexus. However, I tie in with the idea that “what matters to the politics of redistribution is not the level of inequality, but rather the structure of inequality” (Lupu and Pontusson, 2011, 316). Relatedly, Kim (2019) proposes a model of positional concern based on which he argues that one should differentiate between changes in inequality driven by increases in the income gap and increases in the share of low income people. In fact, his model predicts that “when the income distribution is more concentrated at the lower income level, the lower income citizens would more likely vote against the redistribution policy” (Kim, 2019, 33). The theoretical mechanism I present has similar implications regarding the role of the structure of inequality. I argue that the shape of the income distribution matters for my argument insofar as it conditions how tight, and therefore fierce, the competition is.

The *paying for resentment* mechanism rests on the assumption that people care about defending their relative rank and position in the income distribution against those below. It stands to reason that this goal is harder to achieve and therefore the threat more salient the more the competitors are on one’s tail. Therefore, the negative effect on support for redistribution should be stronger where the income distribution is more compressed.⁹ By ‘compressed’ I mean that a larger proportion of the population receives a smaller share of overall income; a definition that guides my variable choice in the next chapter. This is based on a similar justification than the one why the poor would care more about downwards comparisons than the rich: where large income differences are more scarce, they are worth more, and positional competition is fiercer. And, if the distribution is already compressed where those for whom clear downwards

⁹This implication is similar to the one made by Kim (2019) and to some extent with the theoretical argument – but not the empirical design – by Corneo and Grüner (2000).

demarcation means more are situated (i.e. the poor), redistribution would compress it even more. This brings me to the fourth, and final, hypothesis:

Hypothesis 4 (Competition Effect)

The salience of this threat increases when economic competition is tighter, i.e. in a context of a compression in the bottom of the income distribution.

3.3 Formal Model

The presented argument makes a specific proposition about how individuals can diverge from the standard expectation that redistribution preferences follow material self-interest. Therefore, before introducing a social component to people's support for redistribution, a model approximating how much individuals stand to gain materially out of redistribution serves as a starting point. Simply put, individual support for the welfare state will depend on how much they pay into it and how much utility they get out of it. In a general sense, the welfare state is a means to either compensate for a shortfall of income in the present or to insure against a shortfall (loss) of income in the future. The classic and widely-used workhorse model of Meltzer and Richard (1981) introduced a simple flat tax and lump-sum transfer, where the position of each individual relative to the mean determined their support for redistribution: 100% if below the mean, 0% if above. Subsequent approaches have introduced a dead-weight loss to the taxation such that preferred tax rates *range* between 100% and 0% when approaching mean income from below.¹⁰

Given a population of size $\sigma = 1$,¹¹ and assuming a balanced budget, the overall welfare pie is composed of all the payments of tax-payers.

$$\begin{aligned} T(t) &= \bar{y}\sigma\tau(t) \\ &= \bar{y}\left(t - \frac{1}{2}t^2\right) \end{aligned} \tag{3.1}$$

The function $\tau(t)$ represents the dead-weight of taxation by being strictly concave

¹⁰Obviously, this is a stark simplification as it is very hard to capture and formalise all the different ways in which people 'get their money's worth' from modern welfare states. Public goods such as roads, education, music schools, public transport etc. are difficult to quantify as a per capita benefit. However, for all intents and purposes, many theories about social preferences focus on transfer benefits and/or public insurance payments, as a necessary simplification.

¹¹Consisting of native-born citizen (σ_D) and immigrants (σ_I) which together $\sigma_D + \sigma_I = \sigma = 1$

($\tau''(t) < 0$). $T(t)$ goes on to pay for a lump sum transfer to all in society. The utility of individuals is therefore given by their post-tax-and-transfer consumption:

$$V_i = U(c_i) = U((1 - t)y_i + T(t)) \quad (3.2)$$

where y_i represents personal market income. The function $U(c_i)$ is governed by the coefficient of relative risk aversion $\epsilon = -c \frac{u''(c)}{u'(c)}$, which means that $u(c) = \frac{c^{1-\epsilon}}{1-\epsilon}$.¹² It is concave and has the standard properties $u'(c_i) > 0$ and $u''(c_i) < 0$. This means that people have decreasing marginal returns on income, implying that an additional unit of income matters less to a rich person than a poor person. The concavity of the utility function is taken to also mean that people are risk averse.¹³

Taking the first order condition of equation 3.2 yields:

$$t^* = 1 - \frac{y_i}{\bar{y}} \quad (3.3)$$

Therefore, the preferred tax rate is 0% if $y_i \geq \bar{y}$ and, where $y_i < \bar{y}$, a linear decreasing function of income, starting at 100% for $y_i = 0$. In world where only material self-interest matters for individual preferences, support for redistribution is entirely and linearly determined by income. This is shown in Figure 3.2.

3.3.1 Modelling Positional Competition

To translate my argument formally, I complement the utility function in equation 3.2 with a measure of position within the income distribution: relative satisfaction/deprivation. In his seminal book *Relative Deprivation and Social Justice*, Runciman (1966) emphasised the importance of an individual's reference groups for social comparisons, and consequently the sense of injustice felt. Formalised by Yitzhaki (1979), relative deprivation – and its counterpart relative satisfaction – refers to comparisons with

¹²For $\epsilon \in [0, +\infty]$. Risk averseness increases proportionally to ϵ . For $\epsilon = 0$, we have risk neutrality.

¹³Even though not directly related to the current topic, it is worth noting that there has been considerable debate in the behavioural economics literature about the fact that decreasing marginal returns and risk aversion are often modelled in the same way. According to Wakker (1994, 3) “risk attitudes should consist of more than just appreciation of money.” Within non-expected utility theory, decision weights attached to an event potentially occurring are a “measure [of] the impact of events on the desirability of prospect, and not merely the perceived likelihood of these events” (Kahneman and Tversky, 1979, 280). The literature on non-expected utility theory grew out of the problems classical expected utility theory had to adequately reflect people's day-to day decisions (see also: Machina, 1989, 2008; Starmer, 2000; Wakker, 2010).

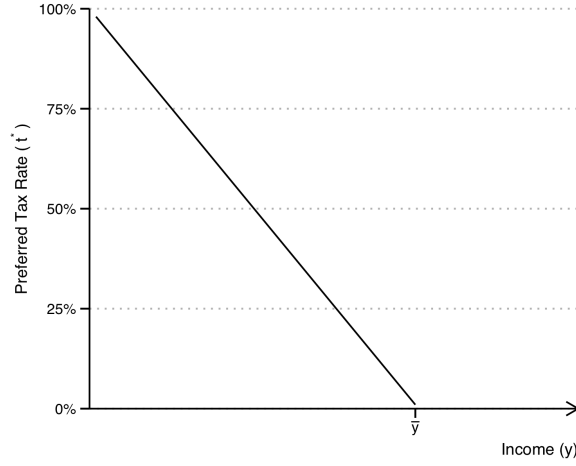


Figure 3.2: Preferred Tax Rate with Material Self-Interest Only

those better off (worse off) and is the average income difference between individual i and all those of the reference group with higher (lower) incomes (see also: Yitzhaki, 1982; Chakravarty and Chakraborty, 1984; Chakravarty, 1997; Bossert and D'Ambrosio, 2006; D'Ambrosio and Frick, 2007). Here, I explicitly focus on downwards comparisons and therefore on relative satisfaction. I argue that the importance of distinct and clear social boundaries is greater for groups 'below' than those 'above' (see also: Rose, 2006, 12-13).¹⁴ Furthermore, even though people probably experience an aggregate of relative deprivation and relative satisfaction at the same time (Stewart, 2006, 785), it is the value derived from relative satisfaction that intuitively might constitute the "social limits to redistribution" (Corneo and Grüner, 2000). This conceptualisation is analogous to Fehr and Schmidt's advantageous inequality, with the important difference that advantageous inequality is actually *preferred* to some extent.

The measure of relative satisfaction is the "mean score difference between individual i and those [below] individual i in the score distribution [multiplied by] the proportion of individuals in the society with scores [smaller] than that of individual i . It is therefore a function of the expected value of the difference between individual i 's score and an individual with a [smaller or equal] score [...] and an individual's position in the score

¹⁴Importantly, Yitzhaki (1979) shows that the "[g]ini coefficient is a quantification of [...] the theory of relative deprivation", in that absolute aggregate relative deprivation in society is a product of the gini coefficient and mean income.

distribution” (Stewart, 2006, 784). Therefore, the utility function now looks as follows:

$$\begin{aligned} V_i &= (1 - q)U(c_i) + \beta G(S_i) \\ &= (1 - \beta)U(c_i) + \beta G\left(\frac{1}{n} \sum_{j=1}^{n_j} (c_i - c_j)\right) \text{ for all } j \leq i \end{aligned} \quad (3.4)$$

where β is the relative weight of positional competition compared to material self interest. This can be rearranged more conveniently as follows:

$$\begin{aligned} V_i &= (1 - \beta)U(c_i) + \beta G\left(\frac{n_j}{n} \frac{1}{n_j} \sum_{j=1}^{n_j} (c_i - c_j)\right) \text{ for all } j \leq i \\ &= (1 - \beta)U(c_i) + \beta G(p_j(c_i - \bar{c}_j)) \text{ for all } j \leq i \\ &= (1 - \beta)U(c_i) + \beta G(p_j(1 - t)(y_i - \bar{y}_j)) \text{ for all } j \leq i \end{aligned} \quad (3.5)$$

This re-arranged equation shows that, as they are formalised here, positional concerns are a function of the proportion of the overall population that is poorer than the individual p_j multiplied with the difference between one’s consumption level and the average consumption level of the part of the population poorer than the individual $c_i - \bar{c}_j$. With a flat tax and lump sum benefit, $c_i - \bar{c}_j$ reduces to the difference in post-tax (but pre-transfer) income $(1 - t)(y_i - \bar{y}_j)$. Kim (2019) models positional concerns slightly differently, namely by only incorporating the “cumulative distribution function of population mass at consumption level c ” (p.31) into individual’s utility function.¹⁵ In contrast, the formalisation adopted here consists both of the ordinal rank within the distribution and a measure of distance to the bottom, which can capture how *tight* the competition is.

The function $G(S_i)$ also has the properties of $G'(S_i) > 0$ and $G''(S_i) < 0$, implying that the marginal relative satisfaction is decreasing (Yitzhaki, 1979, 323).¹⁶ More specifically, the function applies the following CRRA transformation:

$$G(S_i) = \frac{(S_i)^{1-\gamma}}{1-\gamma} = \frac{(p_j(c_i - \bar{c}_j))^{1-\gamma}}{1-\gamma} \quad (3.6)$$

¹⁵Moreover, he explicitly differentiates this from a Keeping-up-with-the-Joneses type of utility, arguing that this would predict a “reversion’ to the comparable consumption level”, limiting “the possibility of incorporating the feature of positional competition” (Kim, 2019, 32).

¹⁶Yitzhaki (1979) actually assumes that “marginal relative satisfaction is a non-increasing function of income”. Here I add the restriction that it is a decreasing function of income.

where $\gamma \in [0, +\infty)$, which affects the shape of the function and therefore formalises the marginal returns from increased income distance and rank $p_j(c_i - \bar{c}_j)$. Depending on the value of γ , the marginal returns will be positive but decreasing. This means that the effect is strongest for those closer to the average income of people poorer than them, as the potential utility loss from decreasing relative satisfaction ($G'(S_i)$) is higher. As shown in Appendix A.1.3, the second order condition of equation 3.5 is then negative. This reflects the idea that those with lower relative satisfaction to begin with have the most to lose from a decrease in income distance. These assumptions are a crucial prerequisite to allow me to make an argument about the changing relative importance of material self-interest and relative satisfaction in the resulting preferred tax rate. If the marginal returns were constant (linear utility function), people would just want to ‘buy more’ of the part that has the highest marginal returns, which would always stay the same. The marginal rate of substitution is determined by assumptions made about the relative size of the risk/inequality aversion parameters. I will come back to this when discussing the income dependent effect.

3.3.2 Positional Competition with Group Heterogeneity

One important aspect about the concept of relative deprivation/satisfaction is that different reference groups can be incorporated in people’s calculations. On this account, I expect that people are more likely to behave in accordance with ‘inequity-seeking types’ when faced with a clearly demarcated out-group. Members of society have multiple reference groups, but can feel quite differently about each. In some sense, reference groups may render individuals myopic about overall inequality, focussing their attention on the comparison with a specific subset of the population. For the present purpose, I decompose the relative satisfaction measure¹⁷ into comparison with domestic population and immigrants poorer than one-self, weighted by their share in the population.

$$V_i = (1 - \beta)U(c_i) + \beta [p_D G(S_{iD}) + p_I G(S_{iI})] \quad (3.7)$$

¹⁷On the additive separability of the index see Bossert and D’Ambrosio (2006).

where:

$$G(S_{iD}) = \frac{(p_{jD}(c_i - \bar{c}_{jD}))^{1-\gamma}}{1-\gamma} \quad (3.8)$$

$$G(S_{iI}) = \frac{(p_{jI}(c_i - \bar{c}_{jI}))^{1-\nu}}{1-\nu} \quad (3.9)$$

$\nu > \gamma$ does not formalise a ‘lack’ of concern about immigrants, but rather that satisfaction relative to immigrants is more important than to the domestic population. Furthermore, a higher ν means that individual i cares more about (i.e. gets more marginal utility from) increases in income distance to immigrants at low levels of relative satisfaction and low income. On the other hand, assuming that $\gamma = \epsilon \frac{c_i - \bar{c}_j}{c_i}$, the effect of relative satisfaction compared to fellow domestic poor is constant across the income distribution. In other words, this means that people, and in particular those with already lower levels of relative satisfaction are more sensitive to decreases in relative satisfaction when immigrants represent a larger share of the population. This would in turn decrease their preferred tax rate. From this it follows that, as the share of immigrants in society p_I increases, the part of relative satisfaction experienced that is due to comparison with immigrants increases, and the constricting effect of relative satisfaction on the tax rate becomes stronger (in particular for the poorer): they would rather get a little less so that they can earn more than that particular social reference point.

3.3.3 Model Results

The preferred tax rate decreases as a consequence of the inclusion of relative satisfaction (c.f. H1).

The addition of this relative inequality to the utility function conceptualises the idea that while people would like to be better off in absolute terms, they also like being better off than those below. These two objectives may ‘pull’ the preferred tax rate in different directions for those below the mean income. This is illustrated by taking the first order condition with respect to the tax rate of equation 3.5.

$$\frac{\partial V_i}{\partial t} = (1 - \beta)(-y_i + \bar{y} - t\bar{y})c_i^{-\epsilon} + \beta p_j(-y_i + \bar{y}_j)(p_j(c_i - \bar{c}_j))^{-\gamma} \quad (3.10)$$

Setting equation 3.10 to zero and solving for t allows us to find the function for the preferred tax rate.

$$t^* = 1 - \frac{y_i}{\bar{y}} + \frac{\beta}{1 - \beta} p_j \frac{(\bar{y}_j - y_i)}{\bar{y}} \frac{c_i^\epsilon}{(p_j(c_i - \bar{c}_j))^\gamma} \quad (3.11)$$

As all j are by definition $\leq i$, $\bar{y}_j - y_i$ will always be negative, except for those who are at the bottom of the distribution, where it is zero. This means that demand for redistribution is ‘curbed’ by the average income distance to those below, weighted by the share of people poorer than i . The term $Q = \frac{c_i^\epsilon}{(p_j(c_i - \bar{c}_j))^\gamma}$ encapsulates the idea that maximising relative position will matter more when one’s relative position is less advantageous to begin with: for a fixed c_i , the term Q will become larger overall if p_j decreases and $\bar{c}_j$ increases. Appendix A.2.1 shows that each total derivative with respect to either individual income or income distance to those poorer is negative, i.e. the model yields $\partial V_i / \partial y_i$ and $\partial V_i / \partial d_i < 0$. This is related to hypothesis 1.

The negative effect of relative satisfaction decreases with income (c.f. H2).

From equation 3.11 we can see that the relative importance of income over relative income position is dependent on the term $Q = \frac{c_i^\epsilon}{(p_j(c_i - \bar{c}_j))^\gamma}$, which is the ratio between the marginal utilities of relative consumption and individual consumption, respectively. For the effect to be constant over income, this term needs to be constant itself, meaning its derivative with respect to y_i should be zero.

$$\frac{\partial Q}{\partial y_i} = \frac{\epsilon c_i^{\epsilon-1} (1-t) (p_j(c_i - \bar{c}_j))^\gamma - c_i^\epsilon \gamma p_j (1-t) (p_j(c_i - \bar{c}_j))^{\gamma-1}}{(p_j(c_i - \bar{c}_j))^{2\gamma}} \quad (3.12)$$

$$\begin{aligned} \frac{\epsilon c_i^{\epsilon-1} (1-t)}{(p_j(c_i - \bar{c}_j))^\gamma} - \frac{c_i^\epsilon \gamma p_j (1-t) (p_j(c_i - \bar{c}_j))^{\gamma-1}}{(p_j(c_i - \bar{c}_j))^\gamma} &= 0 \\ \gamma &= \epsilon \frac{c_i - \bar{c}_j}{c_i} = \epsilon \left(1 - \frac{\bar{c}_j}{c_i}\right) \end{aligned} \quad (3.13)$$

The difference between γ and ϵ then determines how much own income matters compared to relative income. If $\gamma > \epsilon(1 - \frac{\bar{c}_j}{c_i})$, the term $\frac{c_i^\epsilon}{(p_j(c_i - \bar{c}_j))^\gamma}$ in equation 3.11 decreases with income, as the difference between the nominator and the denominator diminishes, and thereby the effect is more important to the poor than the rich. If $\gamma < \epsilon(1 - \frac{\bar{c}_j}{c_i})$, the opposite is true and if $\gamma = \epsilon(1 - \frac{\bar{c}_j}{c_i})$, the importance of the effect

does not vary by income. Notably, γ need not be larger than ϵ for the marginal effect to decrease with income, as $\epsilon(1 - \frac{\bar{c}_j}{c_i})$ will always be $\leq \epsilon$. Figure 3.3 illustrates this assuming an income distribution with a mean of 17,800 euros, a median of 16,200 euros and a Gini coefficient of 0.29. This toy example shows that, even with a γ value of 0.4 and an ϵ of 0.6, the marginal effect of relative satisfaction decreases with income up until the 98th percentile.

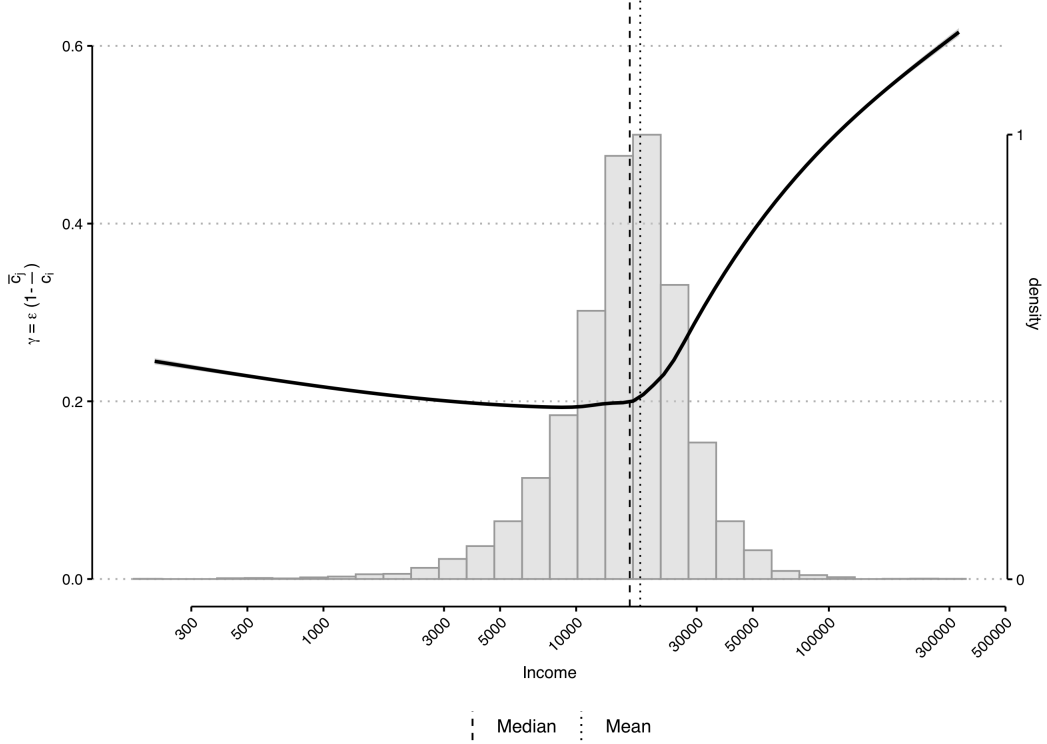


Figure 3.3: Size of γ relative to ϵ

This distribution was created with the GB2 R-package (Graf and Nedyalkova., 2015) based on sampling a generalised beta distribution of the second kind with parameter values $a = 7, b = 19000, p = 0.3, q = 0.5$. This distribution has been shown to be one of the most useful to parametrise and approximate empirical income distributions (see Chotikapanich et al., 2018 or Graf et al., 2011).

Appendix A.2.2 focuses on the cross partial of the tax rate with respect to individual income and individual position. These two are obviously directly connected, and both individually have decreasing marginal returns. The cross partial however is positive which means that the negative effect that distance to the poorer has on redistribution preferences decreases with income. Specifically, it is shown that $\frac{\partial^2 t}{\partial y_i \partial d_i} > 0$. At lower levels of income, and depending on the assumption about the CRRA parameters, the model expects less support for redistribution than in the material self-interest model. As income increases, however, the curvature of the utility function makes it so that this

downwards ‘pull’ loosens progressively. This is further illustrated in Figure 3.4 which depicts the expected preferred tax rate at different levels of income.

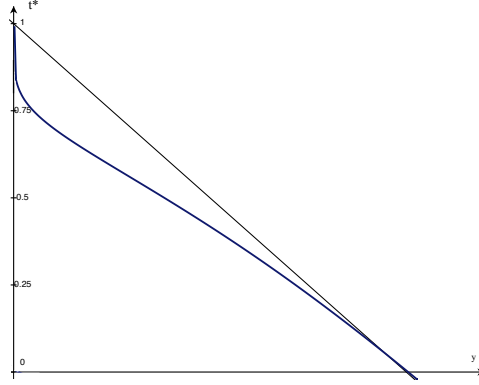


Figure 3.4: Preferred Tax Rate with Material Self-Interest and Relative Satisfaction

The negative effect of relative satisfaction is stronger as the share of immigrants increases (c.f. H3).

This can be shown by taking the F.O.C. of equation 3.7 with respect to the tax rate.

$$\begin{aligned} \frac{\partial V_i}{\partial t} = & (1 - \beta)(-y_i + \bar{y} - t\bar{y})c_i^{-\epsilon} \\ & + \beta \left[p_D(-y_i + \bar{y}_{jD})p_{jD}(p_{jD}(c_i - \bar{c}_{jD}))^{-\gamma} + p_I(-y_i + \bar{y}_{jI})p_{jI}(p_{jI}(c_i - \bar{c}_{jI}))^{-\nu} \right] \end{aligned} \quad (3.14)$$

Setting this to zero gives the following preferred tax rate:

$$t^* = 1 - \frac{y_i}{\bar{y}} + \frac{\beta}{1 - \beta} \left[p_D \frac{\bar{y}_{jD} - y_i}{\bar{y}} p_{jD} \frac{c_i^\epsilon}{(p_{jD}(c_i - \bar{c}_{jD}))^\gamma} + p_I \frac{\bar{y}_{jI} - y_i}{\bar{y}} p_{jI} \frac{c_i^\epsilon}{(p_{jI}(c_i - \bar{c}_{jI}))^\nu} \right] \quad (3.15)$$

Once more, the second order condition is negative, as shown in Appendix A.1.4. For the effect of an increase in the share of immigrants to lead to a lower preferred tax rate, $\partial V_i / \partial d_{iI}$ needs to be *more* negative than $\partial V_i / \partial d_{iD}$. I show in Appendix A.3 that this will be the case as long as $\nu > \gamma$. Therefore, as the share of immigrants p_I increases, the downwards-pulling effect of the relative satisfaction component is activated. The intuitions of this model are shown in Figure 3.5, where it is assumed that $\gamma = 0.7$ and $\nu = 0.9$ and p_I is progressively increased from left to right and first to second row.

According to arguments incorporating altruism, an increase in the share of immigrants would lead the preferred tax rate to follow the material self-interest predictions

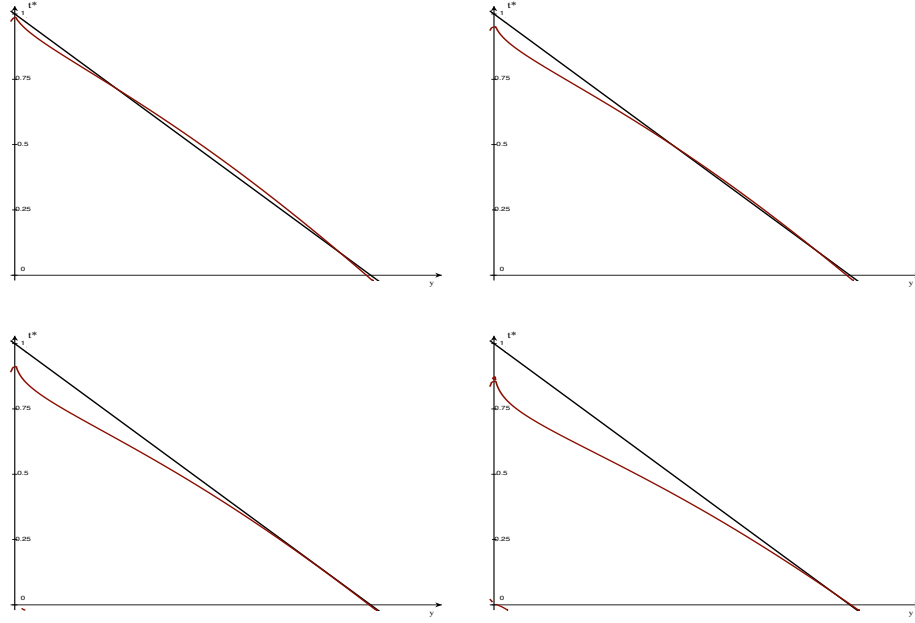


Figure 3.5: Support for redistribution as the share of immigrants increases

more closely (e.g. Alt and Iversen, 2017). In contrast, through the resentment mechanism, the preferred tax rate will *diverge* from material self interest. These figures illustrate how heterogeneity channelled through the resentment mechanism moves and curbs the line for the poor.

3.4 Conclusion

In this chapter, I laid out the theoretical argument of this thesis. As shown here and in the literature review, I am far from the first to consider the role of income, socio-cultural heterogeneity and economic inequality in shaping preferences over redistribution. The contribution of my argument is in the way that these three are theoretically combined. Specifically, I take into account that one's income and its position within the income distribution does not only determine what one can expect to get out of redistribution, but also confers individuals a (social) rank. I suggest that this rank has value to individuals beyond the absolute material costs and benefits it involves. Wanting to preserve the advantageous position relative to those 'below' oneself can therefore be grounds for opposing more redistribution. It leads to willingness to internalise costs – i.e. *pay* for resentment – because the value attached to one's objective material situation also depends on how it compares to others. I surmise that the influence of

this mechanism is non-linearly related to income, and relevant mostly for those lower down the distribution. I hypothesise that increased immigration further increases the salience of relative position, as social differences stemming from sources other than income create expectations that the income distribution should reflect these social ranks. Finally, I argue that the shape of income distribution feeds into the mechanism insofar as it conditions how tight the competition is. If more people are competing for fewer resources, downwards demarcation for the poor should become even more salient.

The mechanism I develop here does not necessarily stand in contradiction with income-dependent (parochial) altruism.¹⁸ According to the argument advanced by Dimick et al. (2017, 2018) and Rueda and Stegmueller (2019), the rich can afford altruism – i.e. forgo some pay-offs to the benefit of others – because of the decreasing marginal returns from income. Conversely, for the poor, material self-interest will dominate over altruistic feelings towards the even less well off. Positional concerns and the ensuing feelings of resentment can be attributed to a different category of social preferences that are based on relative gain maximisation and competitiveness (Messick and Thorngate, 1967; Bolton, 1991). According to these motivational models, people seek to maximise “their relative standing compared to others” (Fehr and Schmidt, 2006, 639) and therefore are willing to forgo some pay-offs to the disadvantage of others. It is likely that people are neither only altruistic nor only competitive; but that they have the latent potential to behave both altruistically or competitively, depending on circumstances. Arguably, income is one of the relevant ‘circumstances’. The rich can afford altruism and the poor are willing to pay for resentment.

In Appendix A.4, I expand my formal model to include a parochial altruism mechanism. I show that both mechanisms can exist jointly in the utility function and not cancel each other out: altruism increases support for the rich (unless the share of immigrants increases) and resentment decreases support for the poor (especially when the share of immigrants increases). For the purpose of illustration, I applied both models to data from the Living Costs and Food Survey (LCF)¹⁹ from the 2016-2017 fiscal year. I calculated the predicted preferred tax rate (proxying support for redistribution) accounting for (a) only material self-interest (b) plus altruism and (c) plus resentment.

¹⁸“A person is altruistic if [...] if her utility increases with the well being of other people” (Fehr and Schmidt, 2006, 638).

¹⁹Office for National Statistics; Department for Environment; Food and Rural Affairs (2020).

The results are shown in Figure 3.6 below. Notably, the model with altruism yields the same prediction than pure material self-interest for the the median income, before predicting higher support for incomes higher than that. Conversely, the model with altruism and resentment predicts lower support than the two other curves for lower incomes.

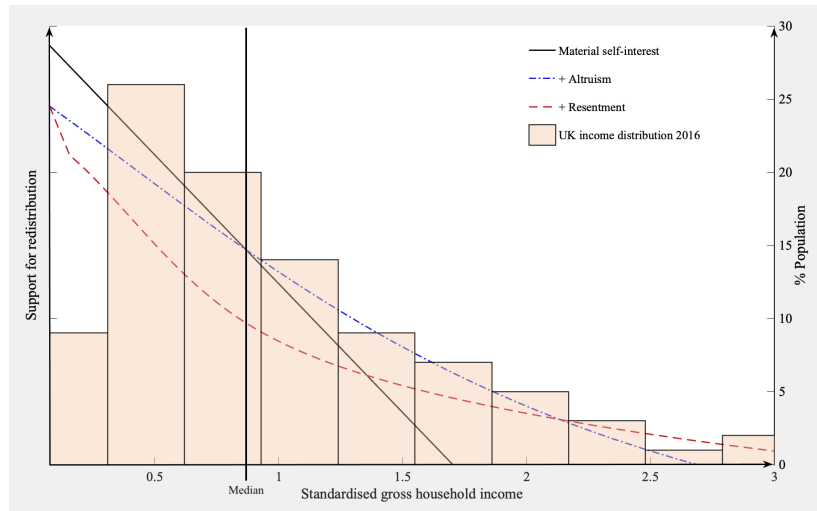


Figure 3.6: Preferred Tax Rate Predicted by the Model in 2016/17 in the UK

Of course, the curves in Figure 3.6 are purely theoretical. The next question is which one best describes observable patterns. I try to answer this question in the next two chapters, in order to establish whether the paying-for-resentment mechanism is a useful way of thinking about people’s calculations behind their preferences. Foreshadowing these next steps, and mirroring Figure 3.6, Figure 3.7 shows the distribution of gross equivalised income of the respondents from the 2016 British Social Attitudes Survey²⁰ and its relationship with support for redistribution. This relationship is modelled parametrically with OLS regression (blue line) and non-parametrically with local polynomial regression (LOESS – red line). It highlights the consequences from assuming a linear bivariate relationship versus one where no deterministic assumption is made about the shape of it. The differences between the two curves are not huge, for sure. Nonetheless, it seems that the linear relationship slightly underestimates the slope of the drop in support for redistribution for income increases at low incomes. Moreover, it also slightly overestimates average support at lower-middle incomes and – notably – near the median income. Even though these are purely suggestive observations, they

²⁰NatCen Social Research (2017).

do speak for a non-linear conceptualisation of the link between income and preferences for redistribution, as the one presented in this chapter.

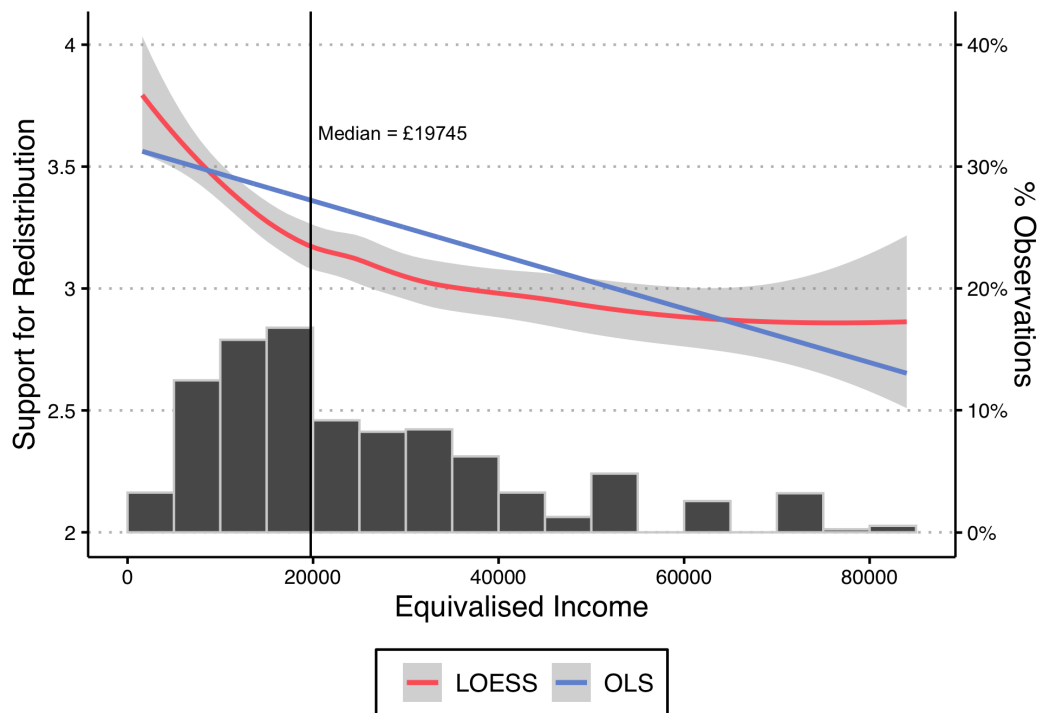


Figure 3.7: Support for Redistribution in 2016 in the UK

Note: Equivalised income is calculated by recoding household income into the bracket midpoints and then divided by the square root of the number of household members. Support for redistributive measures is proxied with approval on a 1-5 Likert scale with the statement: “Government should redistribute income from the better-off to those who are less well off.” Sampling weights are applied.

OBSERVATIONAL EVIDENCE | 4

4.1 Introduction

In order to provide some evidence for my theoretical argument, I first need to establish whether attitudinal patterns follow the empirical implications of said argument. It goes without saying that purely observational data cannot provide precise evidence proving or disproving the exact causal mechanisms hypothesised. However, if these mechanisms do actually hold, it is still important to assess their actual real world relevance and their usefulness in explaining variation in support for redistributive measures across individuals and countries.

As such, this chapter uses survey data from the European Social Survey (ESS)¹ and the International Social Survey Programme (ISSP)² between 2000 and 2019 across 25 European OECD Countries. This data provides me with the dependent variable – individual-level preferences over redistribution – as well as one of the independent variables of interest – income. I combine these with data on population composition by citizenship from the European Labour Force Survey³ aggregated at the national level and data on the distribution of incomes from the World Inequality Database (WID).⁴

With these data I investigate the level of support for redistribution of individuals depending on their income and different levels of immigration and inequality at the macro-level. Specifically, I test whether higher immigration is associated with lower support for redistribution and whether it varies by income. In parallel, I look at the effect

¹European Social Survey (2020, 2004, 2008, 2010)

²ISSP Research Group (2002, 2003, 2017, 2018, 2019b,a, 2021b,a)

³Eurostat (2020)

⁴Blanchet et al. (2021)

of a measure of localised compression of the distribution of income, the share of pre-tax income received by the bottom 50%, as a way of accounting more precisely for the structure of inequality. I also then combine these to see if the income-dependent effects of immigration and inequality interact. According to the theoretical argument, I expect average support for redistribution among the poor to be lower in high immigration contexts and when the share of income of the bottom 50% is low.

Obtained with multilevel regression with random effects by country and by year, the results suggest that, in country-years where immigration was higher, support for redistribution among the poor was slightly but statistically significantly lower. Moreover, in places where the share of income going to the bottom 50% was low, the rich were more supportive. However, where the share of income of the bottom 50% was low, the negative effect of immigration on the *poor's* support for redistribution appeared more pronounced.

I begin this chapter by describing the data, measurement strategies of the variables of interest and control variables in section 4.2. In section 4.3, I then detail the modelling strategy as well as the multiple imputation performed on the data to limit missing data bias. I present the results in section 4.4 and discuss the implications thereof in section 4.5. By the same token, I conclude in section 4.5 as well.

4.2 Description of the Data

The data used in this chapter is a time-series cross-sectional combination of survey data from the ESS and the ISSP. Both of these survey programmes are considered among the best available for the analysis of public attitudes across countries and time. They are widely used within social science, including for research on the determinants of support for redistribution. I use all nine rounds of the ESS as well as eight of the waves of the ISSP which include questions about support for income redistribution by the government. I combine both surveys in order to maximise both temporal and geographic coverage, as well as statistical power for the multi-level regression analysis. Moreover, the two surveys include survey items asking about attitudes to the redistribution of incomes with similar wording. I expand on this in section 4.2.1.

I include in the analysis all European countries that are currently part of the OECD

and the European Free Trade Association (EFTA),⁵ and the United Kingdom.⁶ The choice to include several Eastern European countries could raise concerns about comparability of the level of economic development and the public discourse surrounding redistribution and immigration, which cannot be fully mitigated with regression modelling choices. And yet, this is an issue inherent to all comparative politics research, even when comparing Germany and Austria, for instance. That is not to say that research using survey data from several countries is not useful. On the contrary, if the extent and limitations of what can be said with this kind of data are explicit, such analyses can teach us about how systematic certain patterns of human attitudes and behaviour are, even across very different contexts. Such findings can then inform research within a more restricted scope, or with a more explicit focus on causal inference.

Table 4.1: Data Structure

country	survey	years	n° of waves	n
AT	ESS (8); ISSP (4)	2000-2018	12	21524
BE	ESS (9); ISSP (3)	2002-2018	12	19625
CH	ESS (9); ISSP (6)	2000-2019	15	23459
CZ	ESS (8); ISSP (7)	2000-2019	15	26949
DE	ESS (9); ISSP (6)	2000-2019	15	33930
DK	ESS (8); ISSP (8)	2001-2019	16	22292
EE	ESS (8); ISSP (1)	2004-2018	9	15812
ES	ESS (9); ISSP (6)	2000-2019	15	27487
FI	ESS (9); ISSP (7)	2000-2019	16	24973
FR	ESS (9); ISSP (5)	2003-2018	14	26520
GB	ESS (9); ISSP (6)	2000-2018	15	25737
GR	ESS (4)	2003-2011	4	9542
HU	ESS (9); ISSP (4)	2002-2019	13	18431
IE	ESS (9); ISSP (3)	2001-2019	12	23217
IS	ESS (4); ISSP (4)	2005-2019	8	7470
IT	ESS (5); ISSP (2)	2003-2019	7	12307
LT	ESS (6); ISSP (3)	2009-2019	9	14589
LV	ESS (2); ISSP (5)	2000-2019	7	7974
NL	ESS (9); ISSP (4)	2000-2018	13	21779
NO	ESS (9); ISSP (5)	2000-2019	14	20743
PL	ESS (9); ISSP (2)	2002-2018	11	17438
PT	ESS (9); ISSP (4)	2000-2019	13	20518
SE	ESS (9); ISSP (6)	2001-2018	15	22178
SI	ESS (9); ISSP (7)	2000-2019	16	20646
SK	ESS (6); ISSP (5)	2001-2019	11	16733

⁵Except Luxembourg, excluded due to its particular demography and because only two rounds in total were conducted in this country.

⁶More precisely Great Britain, as Northern Ireland is excluded from the data.

Table 4.1 shows the structure of the data. The country with the least single rounds is Greece with only four ESS rounds, followed by Italy and Latvia with five (two) ESS and two (five) ISSP rounds. For most countries, more than 10 rounds are available, with a median of 13 and a mean of 12.3 survey rounds per country. While these differences in relative sample size and coverage should be kept in mind, the multilevel-modelling I employ for the regression analyses helps mitigate the issue through partial pooling (Gelman and Hill, 2007, 256-259). Moreover, both the ESS and ISSP provide sampling and/or post-stratification weights in most cases.⁷

When aggregating over countries, as I do in some of the descriptives below, I combine these with population weights to account for the different population sizes and the fact that samples with the same size from France and Austria, for example, provide different amounts of information about the overall population of these countries. These population weights are taken from the ESS, averaged across rounds and then combined with both the ESS and ISSP weights.⁸ The summary statistics of sampling and population weights are displayed in Table B.1 in Appendix B.1.

4.2.1 Support for Redistribution

As mentioned previously, the ESS and ISSP surveys are widely used in comparative political research, and notably so when investigating support for redistribution. In fact, many of the works cited in this thesis employ either the ESS or the ISSP to test their propositions. Table 4.2 lists the question wording of the survey items in question and provides a non-exhaustive list of notable research using each survey item respectively.⁹

While there are some slight differences between each survey item, they all mention a) the government as the responsible and b) the reduction of income differences as the measure of interest. The question included in the ESS and in all ISSP rounds except in 2006 and 2016 are also measured on the same Likert-scale from 1-5 (agree strongly - disagree strongly). The survey item included in the ISSP waves Role of Government IV and V (2006 and 2016) is asked with a slightly different framing of the question.

⁷Where no weights were provided, all weights are set to 1.

⁸This procedure directly follows the recommendations laid out by the ESS on weighting when “Combining estimators from multiple rounds and multiple countries”, available here <http://essedunet.nsd.uib.no/cms/topics/weight/4/4.html>.

⁹Figure B.1 provides a graphical representation of the different survey items over time and across countries.

Table 4.2: Support for Redistribution Survey Items

Survey	Question	Response Scale	References
ESS since 2002	<i>“Using this card, please say to what extent you agree or disagree with each of the following statements. The government should take measures to reduce differences in income levels.”</i>	1-5 (agree strongly, agree, neither nor, disagree, disagree strongly)	Jæger (2006, 2013); Finseraas (2008); Rehm (2009); Luttmer and Singhal (2011); Burgoon et al. (2012); Emmenegger and Klemmensen (2013); Burgoon (2014); Marx (2014); Cavaillé and Trump (2015); Häusermann et al. (2016); Cavaillé and Neundorf (2017); Rueda and Stegmueller (2019); Burgoon and Rooduijn (2021)
ISSP 1999, 2000, 2009, 2010, 2017, 2019	<i>“How much do you agree or disagree with the statement: ‘It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes.’?”</i>	1-5 (agree strongly, agree, neither nor, disagree, disagree strongly)	Corneo and Grüner (2000, 2002); Cusack et al. (2006); Scheve and Stasavage (2006); Kenworthy and McCall (2008); Jæger (2009); Ansell (2014); Barnes (2015)
ISSP 2006, 2016	<i>“On the whole, do you think it should be or should not be the government’s responsibility to: Reduce income differences between the rich and poor?”</i>	1-4 (definitely should be, probably, probably not, definitely should not be)	Cusack et al. (2006); Busemeyer (2013); Guillaud (2013); Brady and Finnigan (2014); Gingrich (2014); Beramendi and Rehm (2016); Alt and Iversen (2017)

Instead of asking whether the respondent agrees or disagrees with a statement, she is directly asked her views on the government’s responsibility to redistribute. Moreover, it uses a 4-point answer scale, which impedes the possibility of combining all three items as they are in the analysis. Therefore, I use the two 5-point survey questions as a default, but also create a binary version of the dependent variable from all three survey items as an alternative specification.¹⁰

Table 4.3 summarises the distribution of the combined 5-point ESS and ISSP survey items (with ISSP 2006 and 2016 removed), with the scale reversed so that higher numbers indicate higher support. The country with the lowest average support is Denmark with 3.14, while the country with the highest average support is Greece with 4.34. Across countries, the standard deviation ranges between about 0.7 to about 1.2 points, and the inter-quartile range is, in nearly all cases, situated between the middle and most supportive end of the range. This suggests that there are actually few respondents who

¹⁰With *agree strongly*, *agree*, *definitely should be* and *probably should be* = 1 and 0 otherwise.

Table 4.3: Support for Government Redistribution by Country

country	min	q25	median	q75	max	mean	sd	missing
AT	1	3	4	5	5	3.86	1.07	3.3%
BE	1	3	4	5	5	3.78	1.06	0.91%
CH	1	3	4	4	5	3.59	1.09	1.72%
CZ	1	3	4	4	5	3.54	1.20	3.02%
DE	1	3	4	4	5	3.72	1.07	1.93%
DK	1	2	3	4	5	3.14	1.24	3.8%
EE	1	3	4	5	5	3.92	0.96	1.61%
ES	1	4	4	5	5	4.05	0.91	3.44%
FI	1	3	4	5	5	3.94	1.01	1.72%
FR	1	4	4	5	5	4.03	1.10	1.33%
GB	1	3	4	4	5	3.57	1.05	2.4%
GR	1	4	4	5	5	4.34	0.81	1.84%
HU	1	4	4	5	5	4.29	0.84	1.41%
IE	1	3	4	4	5	3.83	0.97	2.64%
IS	1	3	4	5	5	3.94	1.01	1.66%
IT	1	4	4	5	5	4.12	0.85	2.19%
LT	1	4	4	5	5	4.26	0.76	1.47%
LV	1	4	4	5	5	4.06	0.96	3.66%
NL	1	3	4	4	5	3.47	1.08	2.38%
NO	1	3	4	4	5	3.57	1.02	1.26%
PL	1	4	4	5	5	3.95	1.00	2.14%
PT	1	4	4	5	5	4.25	0.77	1.95%
SE	1	3	4	4	5	3.70	0.97	2.5%
SI	1	4	4	5	5	4.19	0.86	7.28%
SK	1	4	4	5	5	3.99	1.01	1.9%
All	1	3	4	5	5	3.84	1.05	2.41%

explicitly did not agree with the statement. This begs the question of how good these measures are at capturing variation in the degree of support for redistributive measures and is worth keeping in mind throughout this chapter. Nonetheless, these survey items are the best available in terms of measurement validity and reliability for the current purposes.

Figure 4.1 shows the average response to the five-point question over the years included in the data. It suggests that, since the beginning of the 2000s, there has been a mild, but steady increase in support for redistribution from a lowest average score of close to 3.5 up to nearly 4 in 2019. The sharpest increase seems to have happened between 2000 and 2006, while it appears that support has rather plateaued during the Great Recession.¹¹ Figure B.2 shows the nearly same trend with the binary dependent

¹¹This particular lack of sharply increased support for redistribution shown here during that time period is in line with the observations made by Bartels and Bermeo (2014).

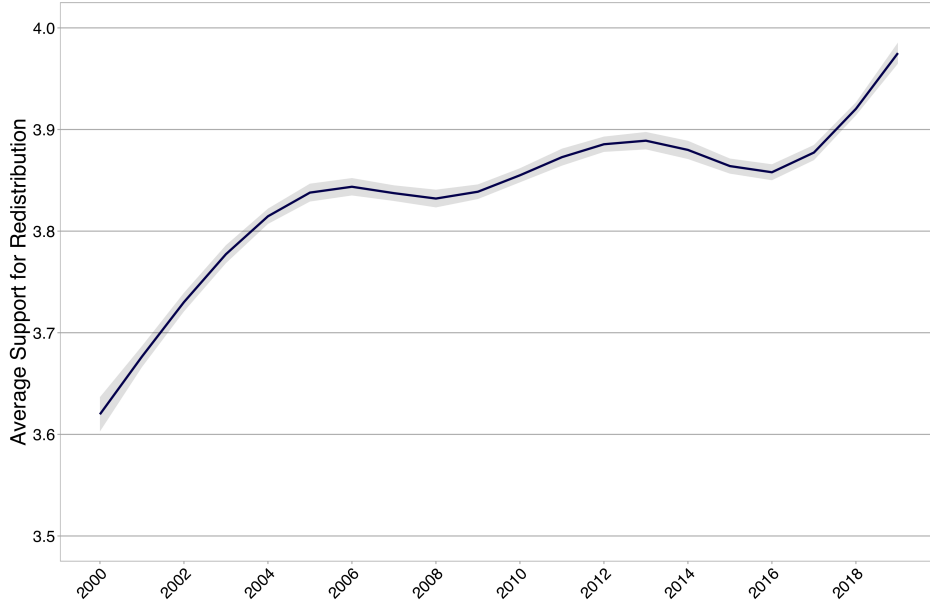


Figure 4.1: Average Response in Data across Time

Note: Estimated using a Generalised Linear Additive Model (GAM) with a smooth term with cubic regression spline and a basis dimension $k = 8$ for time as only predictor. Sampling and population weights applied.

variable, with an overall increase of 65% of respondents selecting an affirmative answer, up to about 76% in 2019.

Figure 4.2 shows the share of respondents supporting redistribution (binary dependent variable) over time by country. Denmark stands out as showing particularly low levels of support though the whole time-period, as does the Czech Republic. Broadly, the Southern and Eastern welfare states exhibit, on average, higher levels of support than the others. Conversely, there appears to be little systematic differences between the Anglo-Saxon, Bismarkian and Scandinavian welfare states.

4.2.2 Household Income

Measures of income in large cross-national surveys often suffer from issues of comparability and consistency (Donnelly and Pop-Eleches, 2018). Asking survey respondents about their income is notoriously a thorny subject, fraught with issues of non-response and social desirability (Yan et al., 2010; Hariri and Lassen, 2017; Angel et al., 2019), and often particularly among high-income respondents (Korinek et al., 2006). Individuals may not know or not want to report their household's precise income, leading to typical non-response rates between 20 and 40% (Yan et al., 2010, 145), as can be seen in Table

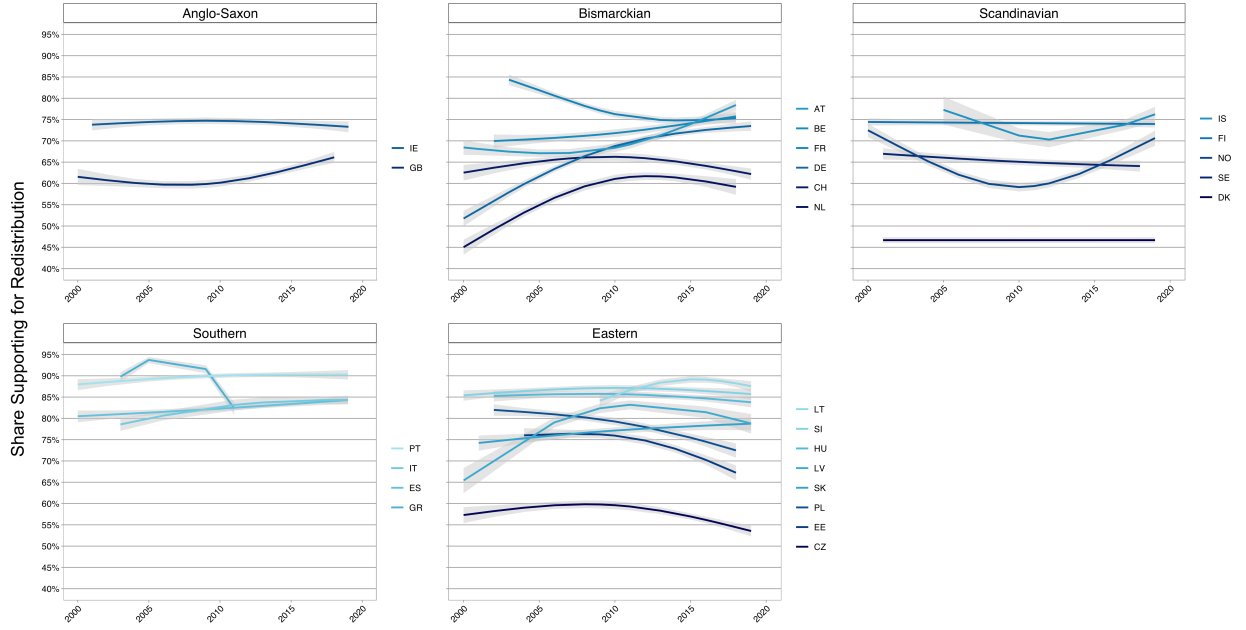


Figure 4.2: Share of Support by Country and Welfare State Type across Time
Note: Estimated using a Generalised Additive Model (GAM) with a cubic regression spline with 5 knots (except for Greece: 3 knots) and random intercepts by country. Scaled weights applied.

4.4 as well.¹²

To mitigate these issues, many surveys often avoid using only open income questions, asking participants instead to indicate in which income bracket they fall. In some cases, for instance ESS rounds 4-9, the threshold of these brackets are the income deciles provided by official national statistics. In other cases, there are more (or less) than 10 brackets and the thresholds are a sequence of incomes with generic intervals, e.g. 1000 euros. The ISSP actually uses a combination of the two methods for some countries, where respondents are first asked to enter their ‘raw’ household income and, if they do not provide an answer, are presented with income brackets. Needless to say, it is not possible to combine these income measures without recoding. To this end, I implement the following procedure:

1. Recode the categorical income variables to the midpoint of their brackets¹³ (Hout, 2004)
2. The highest income category is recoded assuming a bracket twice the size than

¹²It is noteworthy that the Scandinavian countries are among the ones with the lowest non-response rate, below 10%, while the Southern European countries have non-response rates going up to 35% (for Portugal).

¹³For instance, if category 2 indicates a yearly income between 10 000 euro and 20 000 euro, the midpoint is 15 000 euro.

the previous bracket¹⁴

3. If the question asked for monthly or weekly income, multiply by 12 or 52 respectively
4. Once combined with the continuous income measure where applicable, top and bottom code the income distribution within each country-survey-wave by following the Luxembourg Income Study's (LIS) guidelines (Neugschwender, 2020)¹⁵
5. Transform into constant 2015 Euros by correction for inflation¹⁶ and applying purchasing power parities (ppp)¹⁷

Table 4.4: Annual Household Income by Country

country	min	q25	median	q75	max	mean	sd	missing
AT	2000	21500	32300	46200	227200	37500	23800	29.18%
BE	1300	24700	37600	54000	232000	41900	24500	11.11%
CH	2800	39500	57800	82200	261200	65200	36600	19.12%
CZ	900	15200	25000	35200	470100	28300	20400	30.21%
DE	1700	23700	39200	55400	443500	43800	27500	15.49%
DK	1900	30800	54900	82700	179800	59500	36200	8.28%
EE	200	11300	20000	30300	205000	22900	16900	13.16%
ES	600	18000	26500	40400	281100	32200	22900	28.32%
FI	1200	24400	37600	60300	630500	44900	36800	7.68%
FR	1300	23000	35000	54800	451300	43500	38600	13.05%
GB	1000	17200	31000	53800	172300	39900	29900	16.61%
GR	1700	16100	23900	34700	299200	28100	23900	32.27%
HU	700	11400	16800	23800	421900	19500	13900	24.09%
IE	1700	16800	29200	48300	227400	36200	27200	21.79%
IS	1100	32100	49200	70300	691300	57100	42400	25.31%
IT	1400	19300	28200	40700	236500	33100	23700	38.24%
LT	300	8100	14300	21900	123800	16400	11100	19.8%
LV	200	6200	11600	19300	167800	15400	13500	23.45%
NL	1600	24900	37800	54700	217700	42600	25900	11.91%
NO	1000	32400	50000	72300	716700	57100	45700	5.19%
PL	600	13000	19800	28600	476500	24100	21800	19.89%
PT	1500	10600	17600	29300	308400	24300	23400	36.82%
SE	1900	24300	39300	56700	597100	44300	30400	7.07%
SI	1100	16800	27100	39400	313100	30100	20600	25.29%
SK	900	13100	21000	32100	528300	27000	24800	31.82%

Note: All values are rounded to the nearest hundred.

¹⁴For instance, if category 9 is 50 000 euro to 70 000 euro and category 10 is 70 000 euro or higher, the midpoint for category 9 is 60 000 euro, and 90 000 euro for category 10.

¹⁵By setting upper outliers to the exponentiated value of $3 \times$ the logged interquartile range above the logged 3rd quartile and lower outliers to the exponentiated value of $3 \times$ the logged interquartile range below the logged 1st quartile.

¹⁶OECD (2021a)

¹⁷Eurostat (2021)

Table 4.4 summarises the result of these steps. However, total household income is often an imprecise measure of the actual economic well-being and wealth of the respondent due to differences in household size and composition (Buhmann et al., 1988). Therefore, authoritative income databases such as the LIS or the WID consistently apply a correction for the structure of the household or tax-unit (Blanchet et al., 2021). Therefore, I create an equivalised household income measure, whereby I divide the previously recoded total household income by the square root of the number of household members. The summary statistics of the variable used for this transformation are shown in Table 4.5, and the equivalised income distribution by country is shown in Table B.3.

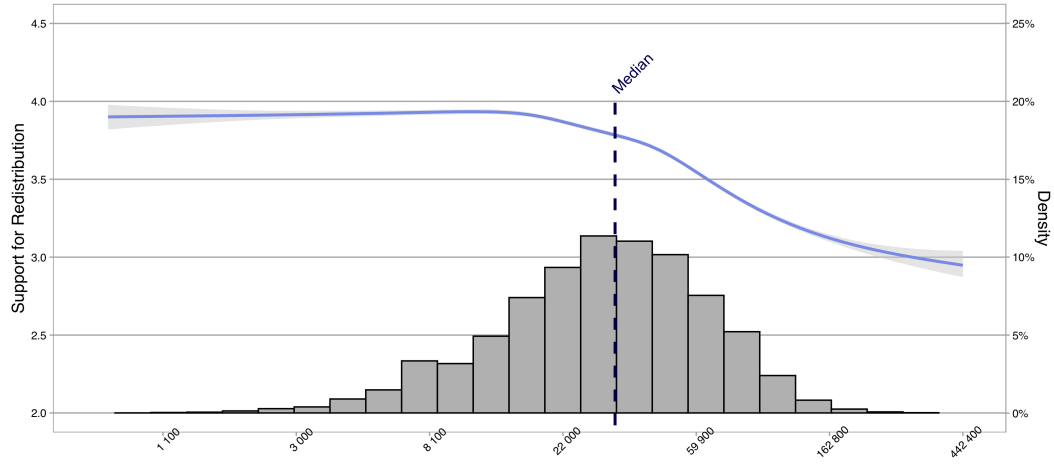
Table 4.5: Household Composition

variable	min	median	max	mean	sd	missing
N ^o of household members	1	2	12	2.641	1.36	<i>0.11%</i>

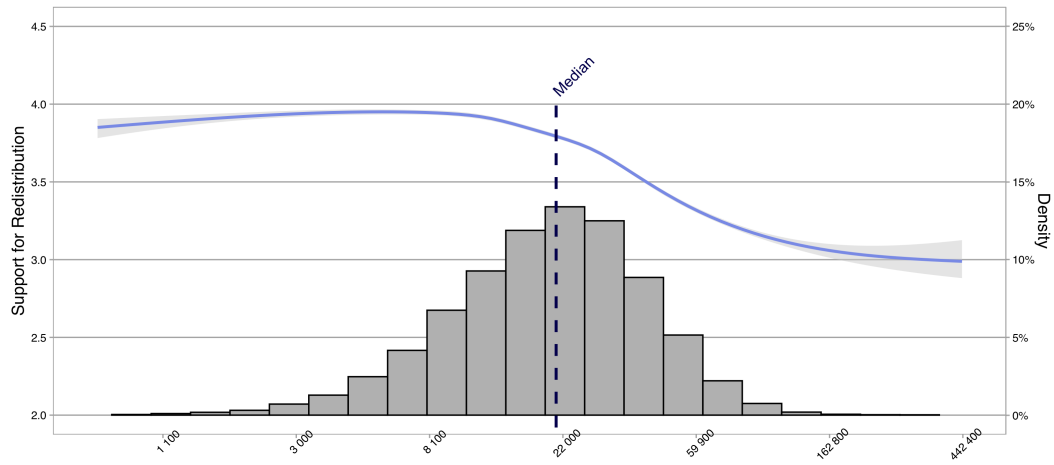
Figure 4.3 shows the distribution of the log-transformed two versions of the income variable. Unsurprisingly, the median income is higher in the untransformed household income version than when correcting for household size. The figure also shows the average level of support for redistribution across the distribution. It is worth noting that, in both graphics, there is little difference in support before the median. While this may be due in part to the fact that people often do not like to use the ends of a scale in surveys, it also is notable that, on average, the poor do not seem to have drastically different preferences than the median income.

Finally, I use these income measures to split the respondents into weighted income deciles within each country and survey wave. These serve as the income variables in the regression models described below. For the reasons outlined above, household income thus measured is likely to be only an imprecise and not very accurate measure of the actual, absolute income of a household. However, it is arguably a better measure of the relative position of respondents within the income distribution. Table 4.6 displays the decile distributions for household and equivalised income. By construction, the share of respondents in each category should be close to 10%.¹⁸ As a comparison point for the level of validity of the survey-based income measure, the table also shows the

¹⁸Slight deviations occur at the margins when ranks are tied.



(a) Household Income



(b) Equivalised Income

Figure 4.3: Average Response Depending on Income
Note: Estimated using a Generalised Additive Model (GAM) with the logarithm of income as a smooth predictor, time and country as random intercepts each. Sampling weights applied.

distribution using threshold values from the WID in each country-year.¹⁹

Table 4.6: Income Deciles

	1	2	3	4	5	6	7	8	9	10
Household Income	11.5%	10.2%	10.3%	10.5%	10.9%	8.7%	8.9%	9.5%	9.5%	10%
Equivalised Income	10.1%	10.4%	10.2%	9.7%	9.7%	10%	9.8%	10.2%	10.1%	10%
<i>WID Thresholds</i>	<i>2.9%</i>	<i>16.2%</i>	<i>9.1%</i>	<i>9%</i>	<i>9.8%</i>	<i>9%</i>	<i>9.9%</i>	<i>9.9%</i>	<i>11.7%</i>	<i>12.5%</i>

4.2.3 Macro-Variables of Interest

The distributions of the variables are shown in Table 4.7. The second column from the right displays the intra-class-correlation (icc) coefficient which represents the share of total variance that is due to between-group (in this case: between country), as opposed to within-group, variation.

Table 4.7: Distributions of Macro Variables

	min	median	max	mean	sd	icc	missing
Short-Term % Change	-2.25	0.42	6.19	0.52	0.84	0.34	<i>4.98%</i>
Medium-Term % Change	-2.86	0.94	7.46	0.96	1.33	0.54	<i>9.2%</i>
Bot. 50 % Pre-Tax Income	15.05	21.76	26.11	21.59	2.28	0.88	<i>0%</i>
Palma Ratio	1.68	2.37	4.4	2.48	0.52	0.81	<i>0%</i>
50/10 Pre-Tax Income Ratio	-1.14	-0.03	2.38	-0.02	0.48	0.75	<i>0%</i>
90/50 Pre-Tax Income Ratio	-0.93	-0.05	1.33	-0.02	0.49	0.91	<i>0%</i>

Changes in the Share of Foreign-born Population I operationalise the level of immigration in a given country-year with the short-time **change** in the share of foreign-born population. I use data from the European Union Labour Force Survey (LFS - Eurostat, 2020) which contains population estimates by country of birth for most countries since 1995. Rather than comparing levels of foreign-born population, I consider the effect of changes in the share of foreign-born population in the four years running up to, and inclusive of, the survey year. Specifically, I subtract the average share in $t - 2$ and $t - 3$ from the average share in the survey year and the year before.²⁰

¹⁹Note that, in some ISSP waves and in some countries, respondents were asked about their gross, not after-tax, income, as is the case in all ESS rounds. Accordingly, I use the WID's pre-tax figures in those cases, and the post-tax series elsewhere.

²⁰Mathematically: $\Delta_{FB_{st}} = \frac{1}{2} \sum_t^{t-1} shareFB_t - \frac{1}{2} \sum_{t-2}^{t-3} shareFB_t$.

Additionally, I also create a measure of medium-term change by subtracting the average share of foreign-born in $t - 4$ until $t - 8$ from the average share from t until $t - 3$.²¹

Figure 4.4 shows, on the left, the share of foreign-born and, on the right, the short-term change in the share of foreign-born with, on each x-axis, the Gini index for market income from the Standardized World Income Inequality Database (SWIID - Solt, 2020). With 25 countries it is difficult to identify each one, but the colours in the figure can nonetheless give an impression of the clustering of the observations within groups, which appears much more severe when looking only at levels of the share of foreign-born.

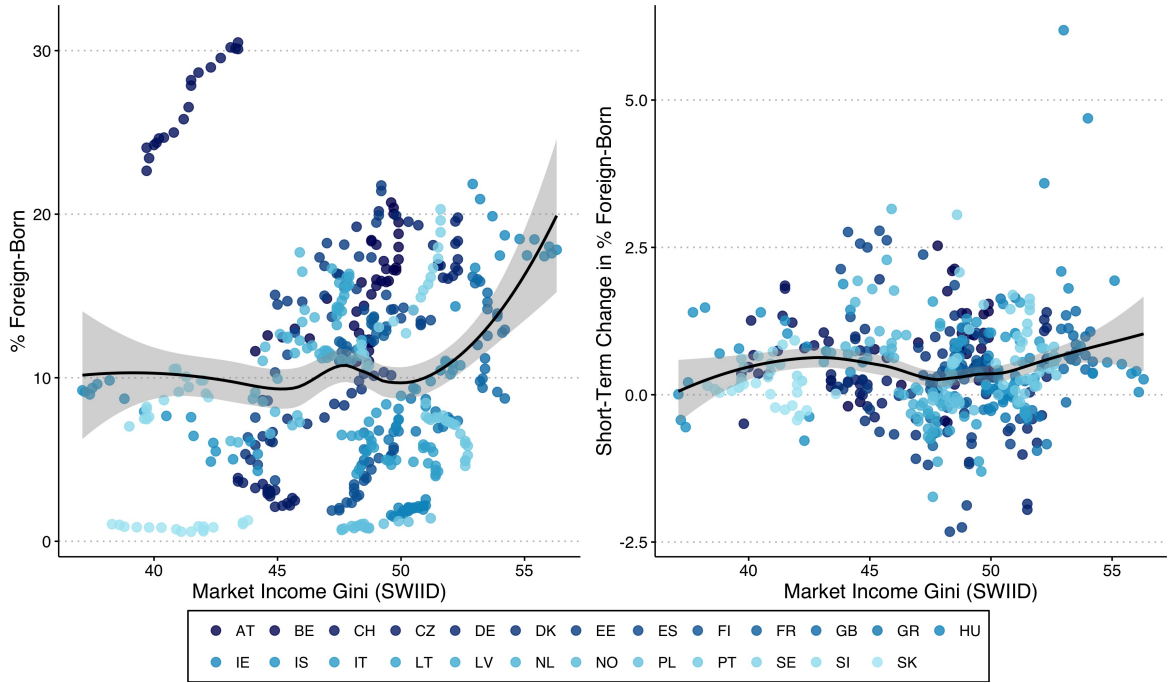


Figure 4.4: Scatterplots of Immigration Measures

This illustrates how, when considering the *levels* of the share in foreign-born population, the variance is mainly attributable to between-country differences, and not within countries over time. This is also reflected in the intra-class-correlation (icc) coefficient displayed in the second to last column in Table 4.7. Accordingly, 89% of the variance in the share of foreign-born is due to between-group (i.e. country) variation, whereas only 34% of variance in short-term changes is between-group variation; and 54% for medium-term changes.

²¹Mathematically again: $\Delta_{FB_{mt}} = \frac{1}{4} \sum_t^{t-3} shareFB_t - \frac{1}{4} \sum_{t-4}^{t-8} shareFB_t$.

Share of Pre-Tax Income by the Bottom 50% Recently, authoritative studies of economic inequality - and in particular the WID - have recommended moving beyond only relying on “synthetic measures of inequality such as the Gini index” (Alvaredo et al., 2018, 27). They argue that the weakness of such summative measures is that they do precisely what they are designed to do: summarise information across all individuals in a society. But this may fail to capture shifts at different places in the income distribution that offset each other’s impact on the inequality index. Instead, they advocate for the use of several metrics of inequality, including the share of income received by specific groups (Alvaredo et al., 2018, 27-28).

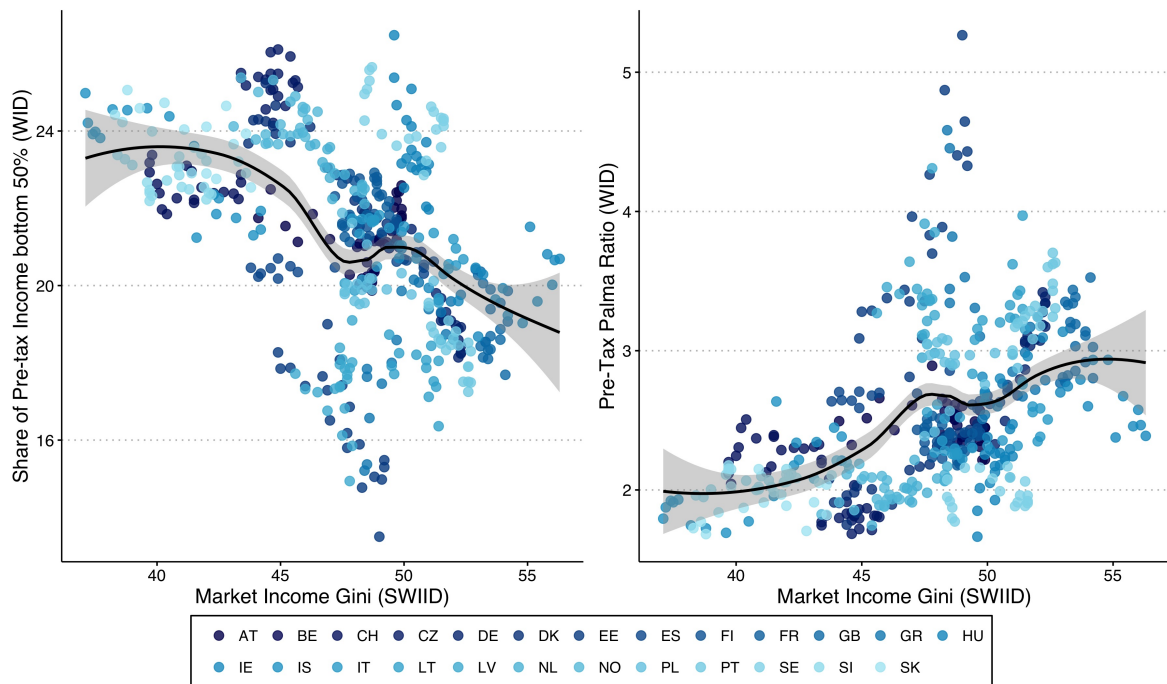


Figure 4.5: Scatterplots of Inequality Measures

Accordingly, I use the WID.world data to retrieve the share of pre-tax national income received by the bottom 50% the countries and years covered in the surveys. This allows me to capture more precisely how income inequality affects the lower part of the income distribution and thereby how ‘compressed’ it is. As can be seen on the left panel in Figure 4.5, a higher share is broadly associated with lower aggregate market income inequality.²² As one alternative measure I also use the Palma Ratio which is the top 10%’s share of income divided by the bottom 40%’s share. The other alternative measures I use in combination are the 50/10 and 90/50 pre-tax income

²²With a statistically significant correlation of -0.48.

threshold ratios.²³ Figure 4.6 illustrates the relationship between the two thresholds across countries and years. The correlation is positive, which means that in countries where the distance between the 10th and 50th percentiles is high, the distance between the 50th and 90th percentiles also tends to be high. The R^2 is 0.48, meaning that only half of each variable's variance is explained by the other. Using these two indicators in the same model allows me to measure the role of 'compression' at the bottom of the income distribution while holding the 'extension' at the top constant.

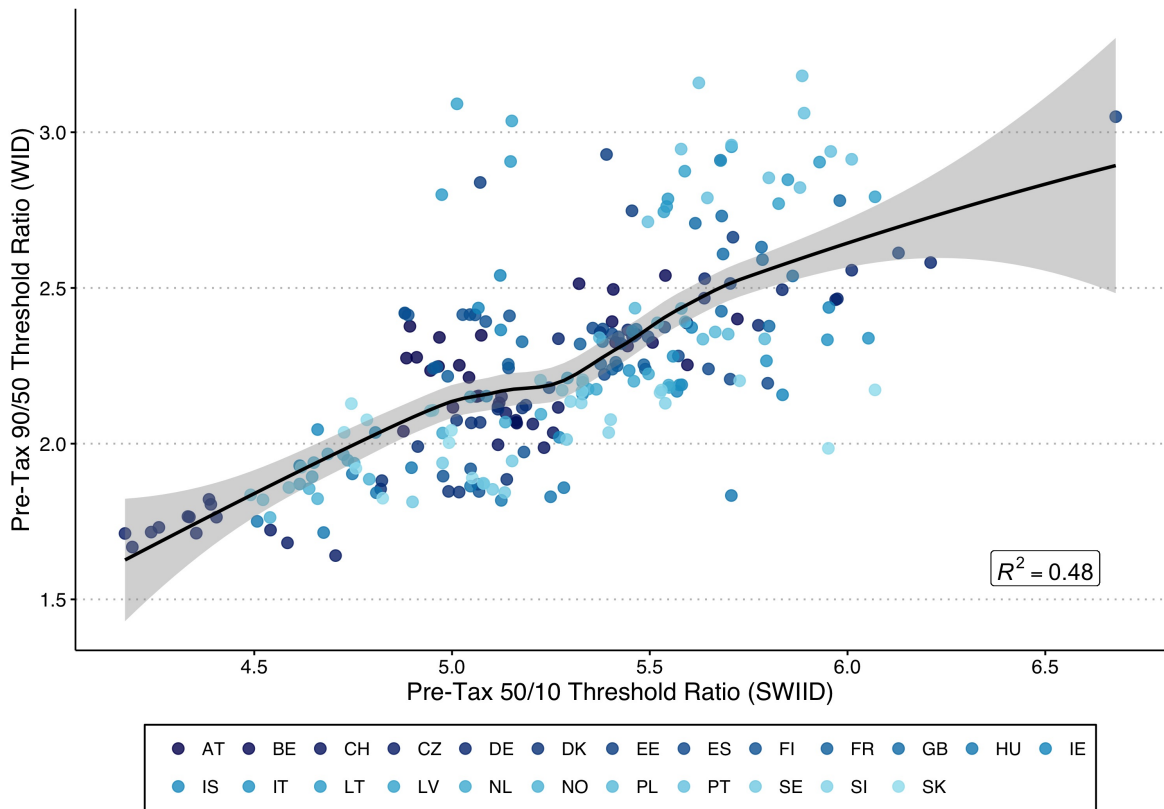


Figure 4.6: Scatterplot of Pre-Tax 50/10 and 90/50 Income Ratios

4.2.4 Control Variables

In addition to the above mentioned variables of theoretical interest, I also include a number of individual and group-level variables to minimise omitted variable bias. At the individual level, I control for socio-demographic variables that have been found to be established explanatory factors (c.f. Stegmueller et al., 2012, 485) and for which information was available in all survey-waves and in all countries. This variables

²³Note that models with these variables do not include Greece as it is an outlier for all the years included in the dataset in the 50/10 ratio.

include age category and gender, a measure of the respondent’s education level (as years of education and as a dummy for university education), a categorical indicator of employment status as well as a categorical indicator of the type of area the respondent lives in.²⁴ These are listed in Table 4.8.

Table 4.8: Individual Controls

variable (cat.)	levels	n	frequency
Gender	man (r)	232150	46.5%
	woman	266566	53.4%
	<i>missing (r)</i>	<i>516</i>	<i>0.1%</i>
Age category	18-34	120233	24.1%
	35-59 (r)	221453	44.4%
	60+	155542	31.2%
	<i>missing (r)</i>	<i>2004</i>	<i>0.4%</i>
Living area	urban (r)	157280	31.5%
	small city	151643	30.4%
	rural	181657	36.4%
	<i>missing (r)</i>	<i>8652</i>	<i>1.7%</i>
University degree	no (r)	368578	73.8%
	yes	126796	25.4%
	<i>missing (r)</i>	<i>3858</i>	<i>0.8%</i>
Employment status	not employed (r)	84169	16.9%
	paid work	262674	52.6%
	retired	123509	24.7%
	unemployed	26312	5.3%
	<i>missing (r)</i>	<i>2568</i>	<i>0.5%</i>
Political orientation	left	137035	27.4%
	centre	127302	25.5%
	right	139536	28%
	<i>dk/missing (r)</i>	<i>95359</i>	<i>19.1%</i>

Note: (r) denotes the levels that are used as reference categories in the regression models.

Even in observational studies, the possibility of post-treatment bias stemming from controlling for “intermediate” outcomes (or: mediating variables) should still be taken seriously (Gelman and Hill, 2007, 188-194), even though the aim is not the estimation of a causal quantity. In a talk in 2010, King defined post-treatment bias as occurring “when controlling away for the consequences of treatment” and “when [the] causal ordering among predictors is ambiguous or wrong”. Most, if not all, socio-demographic variables listed above which I use as controls are found to be associated with a number

²⁴See Shorrock and Grasso (2020) and Bullock (2021) for some recent evidence of the effect of gender and education. Otherwise, see Jæger (2006).

of different political attitudes and beliefs, which in turn are related to attitudes towards government redistribution. For instance, individuals with higher incomes and higher education have been found to believe more strongly in meritocracy, are therefore more tolerant of existing income inequality (Roex et al., 2019; García-Sánchez et al., 2019) and less supportive of redistribution. On the other hand, there is evidence that political ideology has some exogenous effect on preferences over redistribution (Jæger, 2008). In fact, political ideology has been found to have a moderating (rather than mediating) effect (Armingeon and Weisstanner, 2021).

When choosing the relevant controls, the question then is which variables to include to avoid omitted variable bias and which variables to not include to avoid post-treatment bias. This is, to some extent, an unsolvable issue.²⁵ Therefore, I follow the strategy of including only one measure of broad political orientation and avoiding any other ideological controls. The ESS ask respondents to place themselves on a scale from 0 (very left-wing) to 10 (very right-wing) while the ISSP post-coded respondents as left, centre left, centre, centre right or right according to their vote intentions. This difference is obviously not ideal and should be kept in mind when evaluating the validity of this variable. I recoded both these variables into four categories: left, centre, right and don't know/missing, using the latter as the reference category.

At the group-level, the multilevel regression approach with varying intercepts does to some extent 'take care' of inherent differences between countries and years that are not explained by the variables in the model. However, since two of the variables of interest are themselves a group-level variable, confounding at that level may still be a concern. At the same time, there are far fewer degrees of freedom at the higher level (25 countries and 20 years), which restricts the amount of parameters that can be estimated. Therefore, it is important to not saturate the upper-level model (Gelman and Hill, 2007, 294). Controlling, within a regression model, for all possible sources of omitted variable bias at the country-year level so as to recover a plausible *causal* estimate of the effect of immigration and economic inequality on support for redistribution is arguably an impossible feat and one would quickly run into issues of simultaneous causality and other types of endogeneity. As discussed in the introduction, the analyses in this chapter explicitly do not aim towards causal inference, as the kind of data does not allow it.

²⁵In the words of King (2010): "Is there hope? There's always hope; just no answers!"

Table 4.9: Macro-level Controls

(a) Continuous Variables

variable	min	q25	median	q75	max	mean	sd	missing
Social Exp. (%GDP)	12.16	17.84	21.93	25.75	32.03	22.03	4.7	0%
Unemployment rate	2.02	5.01	7.1	9.28	26.12	7.89	4	0%

(b) Welfare State Typology

variable	levels	countries
Ferrera (1996)	Anglo-Saxon (r)	GB, IE
	Bismarckian	AT, BE, CH, DE, FR, NL
	Scandinavian	DK, FI, IS, NO, SE
	Southern	ES, GR, IT, PT
	Eastern	CZ, EE, HU, LT, LV, PL, SI, SK

Instead, I am investigating whether systematic patterns in line with the theoretical intuitions can be found in the data. For these reasons, I keep the upper-level model parsimonious and only control for the unemployment rate²⁶ and the net public social expenditures as a percentage of GDP,²⁷ both from the OECD Database. Additionally, I use the classification proposed by Ferrera (1996) to control for welfare state types. They are displayed in Table 4.9.²⁸

4.3 Estimation Strategy

4.3.1 Multilevel Model

This thesis' argument consists of moving parts moving at different levels. While support for redistribution and household income are measured at the individual level, the income share of the bottom 50% and the share of foreign population vary at the group-level, country-years. Hence, a no-pooling approach with fixed effects for each group is impractical. Any group-level variable will invariably be perfectly co-linear with the country-year dummies, making it impossible to estimate their effects. On the other hand, it is inadvisable not to account for the multilevel structure of the data by completely pooling all observations, as idiosyncratic differences between countries could

²⁶OECD (2021b)

²⁷OECD (2021c)

²⁸I do not include GDP/cap as a control, as it is insignificant across all models.

be driving observed results. As such, multilevel regression is a compromise between no pooling and complete pooling (Gelman and Hill, 2007, 252-253). Moreover, multilevel models decompose the variance into individual and group level variance as well as guarding against the ecological fallacy and thereby provide a more suitable choice than simply using cluster-robust standard errors (Gelman, 2007). Because the data has a time-series cross-sectional structure, a special case of non-nested groupings (Gelman and Hill, 2007, 297), I estimate multilevel models with two sets of varying intercepts - by country and by years. The varying intercept-only model, where individuals i are nested within the overlapping categories of countries j and years t is specified as follows:

$$\begin{aligned} redist_i &= \alpha + \gamma_{j[i]}^{cntry} + \tau_{t[i]}^{year} + \epsilon_i \\ \gamma_j^{cntry} &\sim N(0, \sigma_{cntry}^2), \text{ for } j = 1, \dots, J \\ \tau_t^{year} &\sim N(0, \sigma_{year}^2), \text{ for } t = 1, \dots, T \end{aligned} \quad (4.1)$$

where ϵ_i is the individual-specific residual and α the ‘fixed’ part of the intercept common to all. γ_j and τ_t represent the varying part of the intercept by country and year respectively. They are each assumed to follow a normal probability distribution with means 0 and variances σ_{cntry}^2 and σ_{year}^2 respectively. This means that for all individuals observed in country $j = 1$ and year $t = 2$, for instance, the intercept will be the sum of $\alpha + \gamma_1 + \tau_2$.

All subsequent, multivariate, regression models include equalised income deciles as continuous predictor. To evaluate the role of changes in the share of foreign-born population and of the inequality measures discussed in section 4.2.3, and how their association with support for redistribution depends on income, I estimate the following model:

$$\begin{aligned} redist_i &= \alpha_{j[i],t[i]} + \beta^d edecile_i + \beta^{im} immigr_{j[i],t[i]} + \beta^{in} ineq_{j[i],t[i]} \\ &\quad + \beta^{d.im} edecile_i \times immigr_{j[i],t[i]} + \beta^{d.in} edecile_i \times ineq_{j[i],t[i]} + \epsilon_i \end{aligned} \quad (4.2)$$

To investigate the three-way interaction between income and the two upper-level

variables, I also estimate the following:

$$\begin{aligned}
redist_i = & \alpha_{j[i],t[i]} + \beta^d edecile_i + \beta^{im} immigr_{j[i],t[i]} + \beta^{in} ineq_{j[i],t[i]} \\
& + \beta^{d.im} edecile_i \times immigr_{j[i],t[i]} + \beta^{d.in} edecile_i \times ineq_{j[i],t[i]} \\
& + \beta^{im.in} immigr_{j[i],t[i]} \times ineq_{j[i],t[i]} + \beta^{d.im.in} edecile_i \times immigr_{j[i],t[i]} \times ineq_{j[i],t[i]} + \epsilon_i
\end{aligned} \tag{4.3}$$

In both of these $\alpha_{j[i],t[i]} = \alpha + \gamma_{j[i]}^{cntry} + \tau_{t[i]}^{year}$ and have the same normal distributions for γ_j and τ_t than in equation 4.1.

I estimate all models once without any controls, once with individual-level controls and once with individual and group-level controls. Moreover, all group-level variables are centered and scaled including the immigration and inequality measures by subtracting their respective means and then dividing them by two standard deviations (following Gelman, 2008). First, this allows for a simpler interpretation of the fixed intercept as the average support for redistribution in an ‘average’ country and ‘average’ year. Second, this simplifies the interpretation and comparability of the estimated coefficients as the average difference in the response variable for a two-standard deviations change in the independent variables. Finally, standardizing group-level variables helps with computation and the estimation of the group-level variances.

All multilevel models are estimated with Restricted Maximum Likelihood (REML), as this estimation method has shown to yield unbiased estimates of both coefficients and variances even when the upper-level sample size is small (Elff et al., 2021, 414). Moreover, statistical hypothesis tests are conducted following the recommendations of Elff et al. (2021), who argue that assuming a standard-normal distribution of test statistics for the estimates of upper-level predictors is inappropriate. Instead, they recommend relying on the Satterthwaite method or the ‘ $m - l - 1$ rule’.²⁹ Both of these adjust the degrees of freedom for group-level variables as well as cross-level interactions for the t -statistic.

In appendix B.6, I present the figures based on the main model specifications but with country-fixed effects and a linear time trend instead of the multilevel models. The results and conclusions that can be drawn from them are very similar to those with the

²⁹:[W]here m refers to the number of upper-level units and l refers to the number of contextual variables, that is, to the number of observations and independent variables in a group-level approximation of the contextual relationships in a multilevel model, respectively.” (Elff et al., 2021, 416)

varying-intercepts. However, the standard errors are significantly smaller if they are not clustered, and a bit larger if clustered by country.

4.3.2 Multiple Imputation

Another aspect that guided my choice of variables and their re-coding was to minimise missingness wherever possible. Unfortunately, very little can be done about the high non-response rates to the household income question. Even more, the non-trivial variation in these non-response rates by country shown in Table 4.4 further challenge the meaningfulness of any results based on this data. Therefore, I deal with missingness by performing multiple imputation on the survey data. Honaker and King (2010, 561) summarise the procedure as follows:

The idea is to extract relevant information from the observed portions of a data set via a statistical model, to impute multiple (around five) values for each missing cell, and to use these to construct multiple ‘completed’ data sets. In each of these data sets, the observed values are the same, and the imputations vary depending on the estimated uncertainty in predicting each missing value.

This method has been shown to lead to more reliable inferences than list-wise deletion or mean-imputation (King et al., 2001), and is implementable with the package `amelia` (Honaker et al., 2021).³⁰ Accordingly, I create five imputed sets of data, on which I fit the same models as on the original data with the missing values. The results based of each imputed dataset are then combined following King et al. (2001) to yield a point estimate for any quantity of interest q :

$$\bar{q} = \frac{1}{m} \sum_{j=1}^m q_j \quad (4.4)$$

where m is the number of imputations, and q_j the estimate for each imputation. The standard error is “the average of the estimated variances from within each completed data set, plus the sample variance in the point estimates across the data sets (multiplied

³⁰This method has also been used in research on support for redistribution by Iversen and Soskice (2001), Linos and West (2003), Houle (2009), Stegmueller et al. (2012), Haggard et al. (2013), Barnes (2015) and Rueda and Stegmueller (2016).

by a factor that corrects for bias because $m < \infty$)” (King et al., 2001, 53):

$$se(\bar{q}) = \sqrt{\frac{1}{m} \sum_{j=1}^m se(q_j)^2 + (1 + \frac{1}{m}) \frac{1}{m-1} \sum_{j=1}^m (q_j - \bar{q})^2} \quad (4.5)$$

Table 4.10 shows the distribution of household income for the original and for each of the imputed data-sets. Of note is that both the mean and median are slightly lower and the standard deviation slightly higher than in the original data. The relative densities of the observed and the mean of the imputed values for household income and the redistribution item are shown in figures B.4 and B.5.

Table 4.10: Household Income across Imputed Datasets

dataset	min	q25	median	q75	max	mean	sd	missing
Original	227	17950	30890	51260	716740	38780	31550	19.56%
Imputation 1	227	17480	30050	49980	755910	38270	31940	0%
Imputation 2	227	17480	30030	49930	716740	38270	31970	0%
Imputation 3	227	17470	30040	49900	765520	38250	31890	0%
Imputation 4	227	17480	30060	49980	921000	38290	31960	0%
Imputation 5	227	17480	30050	49980	946360	38260	31920	0%

4.4 Regression Analysis Results

I begin by estimating an empty, varying intercept-only model to assess the proportion of variance to be found at each level. The variance decomposition shows that 7.98% of variation of the response variable is due to differences between countries, and another 0.18% to differences between years, for a total of 8.2% of variance found at the upper level. Figure 4.7 shows the distribution of the intercepts estimated with the null-model. The countries are ordered by the level of predicted average support for redistribution.

Table 4.11 shows the combined results of the multilevel regression models fitted on the imputed data.³¹ They include as predictors, first, only income in the form of equivalised income deciles (models 1-3), second, adding the change in the %foreign-born and the pre-taxes and transfers income share of the bottom 50% (models 4-6), and, third, their respective interaction with income (models 7-9). Within those three iteration, one

³¹The results based on the original data with the missing values are shown in Appendix B.2, and display similar patterns.

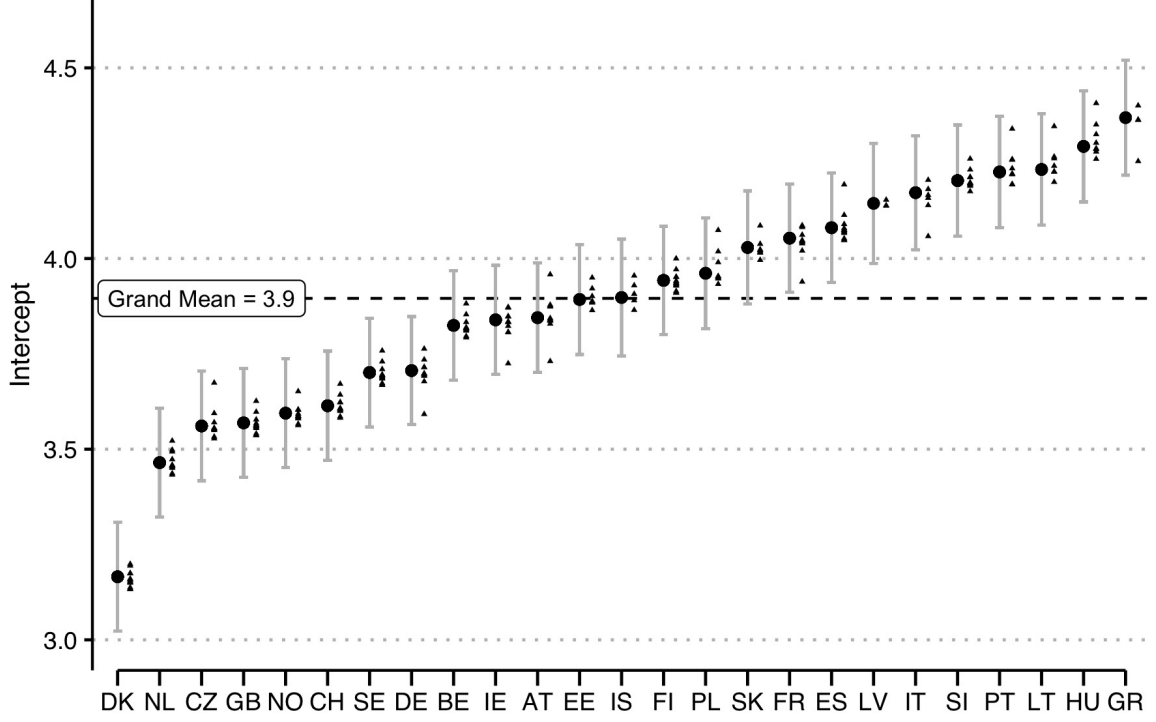


Figure 4.7: Country and Country-Year Random Intercepts from Null-Model

Note: The horizontal, dashed line indicates the estimated fixed intercept (i.e. the grand mean). The larger dots represent the country-specific intercepts that combine the fixed intercept and the random effect for each country. Their 95% confidence interval is in grey. The smaller, triangular dots further indicate the country-year-specific intercepts, which are the sum of the fixed intercept, the country random effect and the year-specific random effect.

model is estimated without controls, one with only individual level controls, and, finally one with individual and macro-level controls.

All models are estimated on the same amount of observations. The intercept can be interpreted across all models as the predicted support for redistribution for an individual in income decile 0 and, where applicable, belonging to the reference categories of all individual-level controls, in a country and a year at the centre of the upper-level distributions and, where applicable, where the macro-level controls are at their means. The intercept standard error represent the square root of the variance parameters σ_{cntry}^2 and σ_{year}^2 . Expressing them as standard deviations rather than variances simplifies the interpretation: the models estimate that the average response to the redistribution item in any given country in the sample will, on average, be about a quarter to a fifth of a point on the 1-5 scale away from the intercept; about 0.05 points away from the intercept in any given year. The Log-Likelihood, AIC and BIC, as relative measures

of model performance, all show small increases in the predictive performance as the models include more parameters.³²

The last row in each table lists the marginal R^2 proposed by Nakagawa and Schielzeth (2013) for mixed-effect models, which represents the proportion of variance explained by the fixed effects only. These suggest that, by itself, a respondent's income decile explains 2% of variance,³³ all individual-level controls together account for about 4.4% of variance, the upper-level controls for about 3% and the two macro-level variables of interest for around 1%. While it is not the aim of this analysis to explain as much variance in support for redistribution measured as such as possible, these marginal R^2 are noticeably low. Model 9, which includes all variables of interest as well as all individual and upper-level controls is only just below 0.1 - implying that only about 10% of the variance is explained with this model. For sure, any model performance metric's meaning can only be evaluated *relative* to other possible specifications on the same data, therefore the *absolute* level of the variance explained by the models' fixed effects should not be taken as representative of the models' usefulness. It is nonetheless noteworthy how much difference in these survey respondents' responses to the 5-point survey item on income redistribution remains unexplained.

Turning the spotlight now on the estimated coefficients, the models all suggest a negative and statistically significant effect of income decile on support for redistribution. Models 1, 4 and 7 yield a coefficient of about -0.05, implying that, respondents in the lowest income decile tend to be about half a point more supportive of redistribution than the highest decile, as measured by the 1-5 scale survey item. This effect is slightly smaller when controlling for the other individual-level factors. Accordingly, all else being equal, the poorest tend to be about a third of a point more supportive of redistribution than the richest. The estimate for income decile does not, however, change much when including any of the group-level variables. This is due to the way income is operationalised: as decile rank, rather than the actual monetary amount. This does away with differences in income levels between countries and across years and, what is more, this income variable is *by construction* uncorrelated with any country- or year-level variable. Moreover, as all continuous macro-level variables and controls are

³²The most complex model (9) has a log-likelihood of $-699,645$, which implies an average likelihood given the estimated parameters for any given data point of $e^{\frac{\ell}{n}} = 0.234$. In comparison, the null-model yields an average likelihood value of 0.226 and model 1 of 0.229 for any given data point.

³³This is not including the survey-dummy.

Table 4.11: Multilevel Regression Results - Imputed Data

	<i>Dependent variable:</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income Decile	-0.053*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.053*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.053*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)
$\Delta\%$ Foreign-born				-0.005 (0.004)	0.002 (0.004)	0.015*** (0.004)	-0.057*** (0.007)	-0.045*** (0.007)	-0.032*** (0.007)
Share Bottom 50%				-0.126*** (0.011)	-0.129*** (0.011)	-0.132*** (0.012)	-0.057*** (0.013)	-0.061*** (0.012)	-0.064*** (0.013)
Decile $\times$ $\Delta\%$ FB							0.01*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
Decile $\times$ Share Bot.50%							-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)
Intercept	4.172*** (0.055)	4.077*** (0.052)	3.912*** (0.145)	4.17*** (0.05)	4.077*** (0.048)	3.867*** (0.139)	4.171*** (0.05)	4.078*** (0.048)	3.868*** (0.139)
Intercept Std. Error	0.268	0.252	0.205	0.247	0.232	0.195	0.247	0.232	0.195
Country									
Year	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
Survey Dummy	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual-level Controls		✓	✓		✓	✓		✓	✓
Macro-level Controls			✓			✓			✓
Observations	482,055	482,055	482,055	482,055	482,055	482,055	482,055	482,055	482,055
Log Likelihood	-710,613	-699,839	-699,813	-710,557	-699,776	-699,742	-710,456	-699,679	-699,645
AIC	1,421,237	1,399,713	1,399,674	1,421,131	1,399,591	1,399,536	1,420,932	1,399,402	1,399,346
BIC	1,421,304	1,399,913	1,399,940	1,421,219	1,399,813	1,399,824	1,421,043	1,399,646	1,399,657
Marginal R^2	0.021	0.063	0.095	0.025	0.068	0.096	0.026	0.069	0.097

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

centred at their mean, including the cross-level interactions in models 7 to 9 also does not affect the main effect of income.

Models 4 to 6 introduce the short-term change in the share of foreign-born population and of the share of pre-tax income received by the bottom 50% as linear effects. The coefficient of the first is not statistically significant in models 4 and 5. Only when controlling for the variables at the upper level is it statistically significant and positive, albeit substantively small. In comparison, the coefficient for the income share of the bottom 50% is negative and statistically significant and robust to the inclusion of controls. According to model 6, a two-standard deviation positive difference in the variable is associated with a 0.13 point decrease in average support for redistribution. This is in line with findings that, in places where income inequality is higher - measured here by a lower share of pre-tax income going to the poorest 50% - average support tends to be higher (see, for instance, Kenworthy and Pontusson, 2005; Huber and Stephens, 2014).

Models 7 to 9 include the two cross-level interactions of income with these variables. It is noteworthy that, while the change in the share of foreign-born appears to have no effect on its own, its main effect is now negative and statistically significant. This is relatively robust to the inclusion of controls, although the absolute effect size decreases slightly. The size of the main effect of the income share of the bottom 50% is about halved in comparison to the models without interaction, yet remains negative and statistically significant. The more interesting aspect of these results however is to be found in the interactions. Since nobody has ever enjoyed writing out a regression equation with interactions, I rely on graphical illustrations of their implications.

Figure 4.8 presents the interaction of income decile with the over-four-year-change in the percent foreign born based on model 7. Panel (a) shows the estimated coefficient of the macro-level variable conditional on the respondent's equivalised income decile. It shows a negative and statistically significant coefficient for deciles 1 through 5, zero effect for deciles 5 and 7, and a positive and statistically significant effect for deciles 8 to 10. According to these results, the poorest respondents surveyed in a country-year with a positive change in the percent foreign-born by 2 standard deviation³⁴ will tend to have an average score on the 5 point redistribution survey item 0.06 points lower.

³⁴Which is equivalent to an increase of about 1.68 percentage point increase in the share of the foreign-born population in the last two years compared to the previous two years.

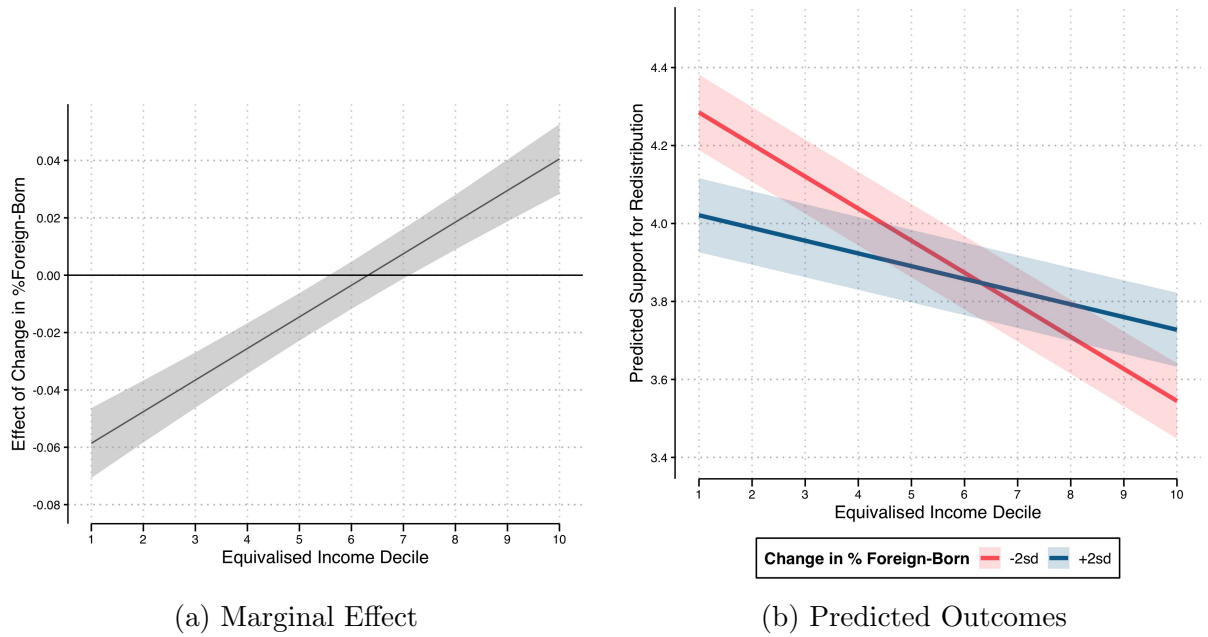


Figure 4.8: Interaction of Income and $\Delta\%$ Foreign-Born
Note: Point estimates based on model 7 with 90% confidence intervals.

On the face of it, this appears to be a substantively small effect. However, this is about the effect that the models without individual controls predict for a one income decile difference. The right hand panel illustrates what this implies in terms of predicted outcomes. Notably, the difference in predicted support for redistribution appears to only be statistically significant for the two poorest deciles. The lines of the point estimates then cross each other at the income level where the coefficient becomes positive, as seen in the left hand panel. The model predicts that, for respondents in the lowest decile, those in a country-year where the change in % foreign-born was two standard deviations above the mean will be about a quarter of a point less supportive of redistribution than those in a country-year where the change in % foreign-born was two standard deviations below the mean.

Figure 4.9 shows the equivalent plots for the interaction between income decile and the share of income of the bottom 50%. The left hand panel again displays the estimated marginal effect conditional on income. It shows that the effect for one unit change in the macro-level variable is negative and statistically significant at all income levels, but more so for the rich than the poor. The model predicts that respondents in the highest deciles are, on average, a fifth of a point less supportive of redistribution (again, as measured on the 1-5 scale) in country-years where the share of pre-tax income

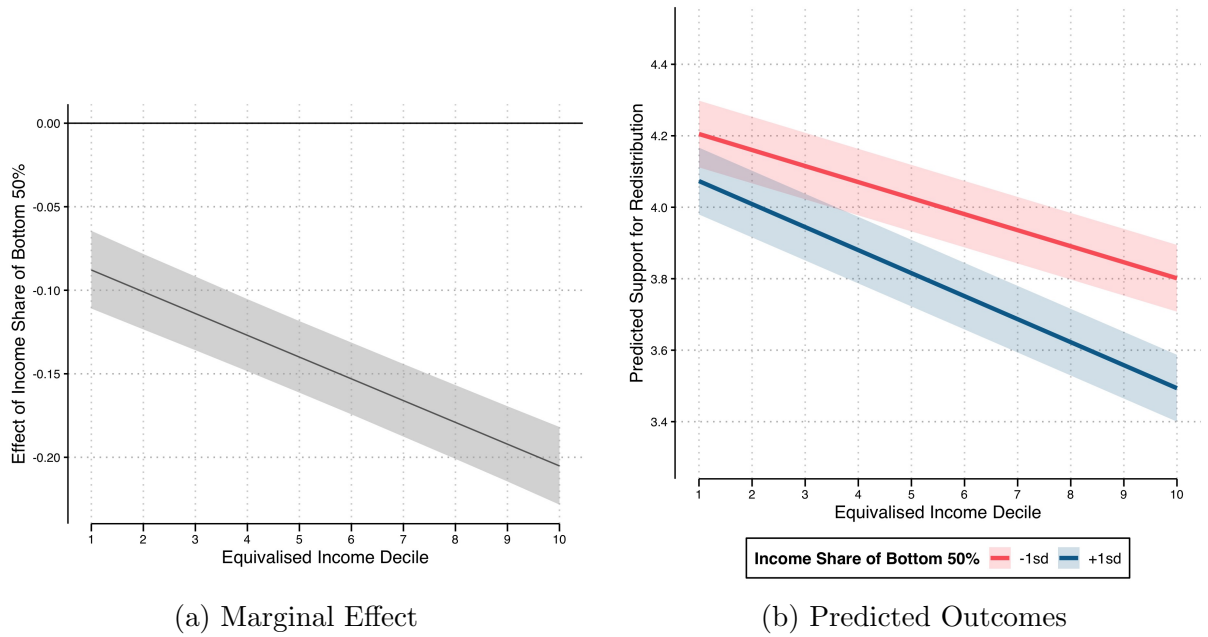


Figure 4.9: Interaction of Income and Income Share of Bottom 50%

Note: Point estimates based on model 7 with 90% confidence intervals.

received by the bottom 50% is about 4.5 percentage points³⁵ higher. In contrast, the difference for respondents in the lowest decile is estimated to be a bit less than a tenth of a point. Panel (b) then shows the predicted support for redistribution by income in places where the share of the bottom 50% is one standard deviation lower compared to places where the share of the bottom 50% is one standard deviation higher than the mean. In contrast to the other variable, the difference in predictions is larger and only statistically significant for higher income deciles. This pattern is in line with arguments and findings that it is the rich that tend to show more significant support in the face of more inequality than the poor (Dimick et al., 2018; Rueda and Stegmueller, 2019).

I now turn to investigating how these two interactions interact. Table 4.12 shows the results of expanding the regression models to include the three-way interaction between income decile, the change in the share of foreign-born and the share of income going to the bottom 50%. According to these, the main effects and two-way interactions are similar in size and statistical significance to those in models 7, 8 and 9 in Table 4.11. Moreover, the interaction between the two macro-level variables appears to be statistically insignificant and the three-way interaction is only significant after inclusion of the individual-level controls, although one should be careful to draw inferences from

³⁵I.e. two standard deviations.

Table 4.12: Multilevel Regression with Three-Way Interactions - Imputed Data

			<i>Dependent variable:</i>		
			Support for redistribution		
			(10)	(11)	(12)
Income Decile			−0.053*** (0.001)	−0.039*** (0.001)	−0.039*** (0.001)
$\Delta\%$ Foreign-born			−0.052*** (0.008)	−0.047*** (0.008)	−0.032*** (0.007)
Share Bottom 50%			−0.056*** (0.013)	−0.062*** (0.012)	−0.064*** (0.013)
Decile $\times$ $\Delta\%$ FB			0.01*** (0.001)	0.01*** (0.001)	0.009*** (0.001)
Decile $\times$ Share Bot.50%			−0.012*** (0.001)	−0.012*** (0.001)	−0.012*** (0.001)
$\Delta\%$ FB $\times$ Share Bot.50%			0.023 (0.016)	−0.013 (0.015)	−0.018 (0.015)
Decile $\times$ $\Delta\%$ FB $\times$ Share Bot.50%			0.001 (0.002)	0.005** (0.002)	0.005** (0.002)
Intercept			4.171*** (0.05)	4.078*** (0.048)	3.868*** (0.139)
Intercept Std. Error	Country		0.247	0.233	0.196
	Year		0.04	0.044	0.044
Survey Dummy			✓	✓	✓
Individual-level Controls				✓	✓
Macro-level Controls					✓
Observations			482,055	482,055	482,055
Log Likelihood			−710,458	−699,683	−699,645
AIC			1,420,941	1,399,415	1,399,346
BIC			1,421,074	1,399,681	1,399,657
Marginal R^2			0.026	0.069	0.097

Note:

*p<0.1; **p<0.05; ***p<0.01

the coefficients and their p-values alone. Even more than writing up a regression equation with two-way interaction, nobody has really ever enjoyed writing up one with three-way interactions. Therefore, I once more turn to a graphical illustration of the associations.

Figure 4.10 shows the predicted support for redistribution depending on income in country-years where the income share of the bottom 50% is, on the left hand side, one standard deviation below the mean ($\approx 19\%$) and one standard deviation above the mean ($\approx 24\%$) on the right. These subplots then each show the predicted response

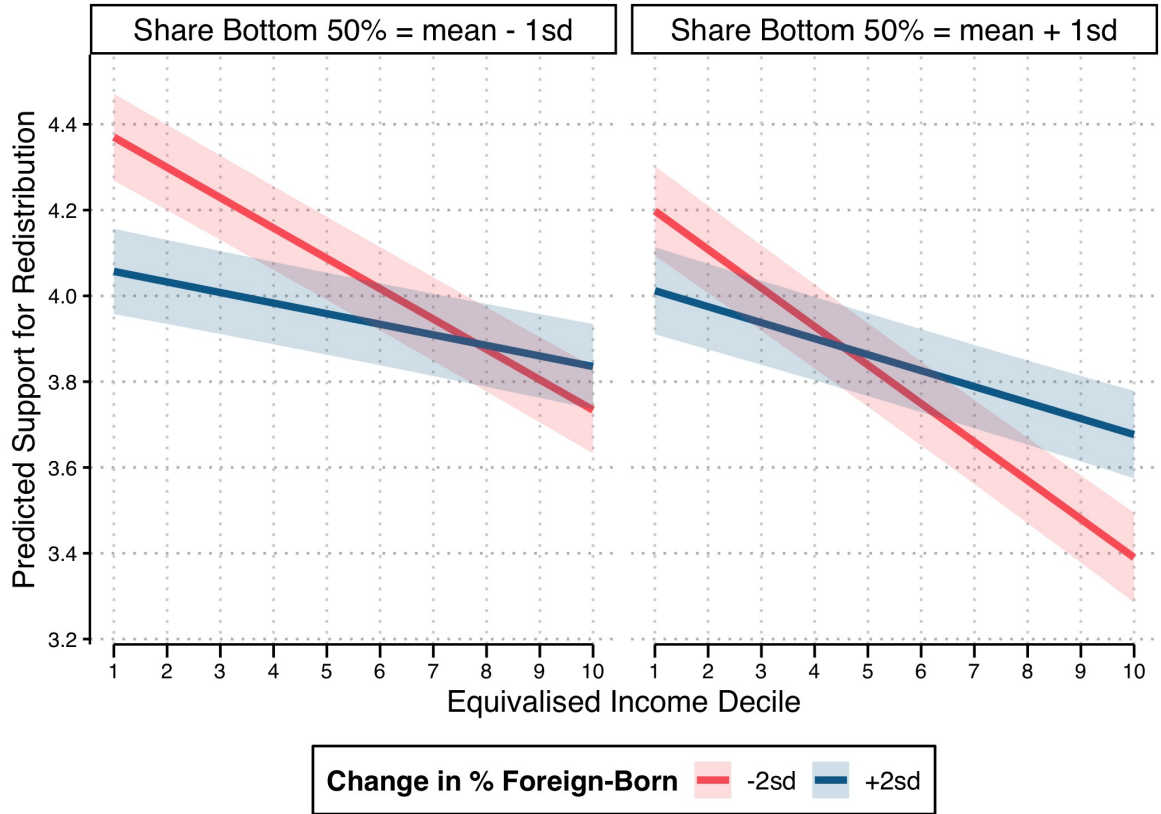


Figure 4.10: Predicted Outcomes with Three-Way Interaction I

Note: Point estimates based on model 10 with 90% confidence intervals.

in two scenarios where, (1), the recent change in the % foreign-born is two standard deviations below the mean ($\approx -1.2\text{pp}$ on the original scale) and, (2), the recent change in the % foreign-born is two standard deviations above the mean ($\approx +2.2\text{pp}$ on the original scale). Notably, the pattern observed in Figure 4.8 - whereby the poor seem less supportive of redistribution in a context of more immigration - is mainly discernible in the left hand panel - where the bottom 50% receives a *smaller* share of pre-tax income. Indeed, the results suggest that the poorest three income deciles tend to be statistically significantly less supportive of redistribution when the bottom 50% are poorer on a macro-level and recent immigration has been increasing. On the right hand panel, where the income share of the bottom 50% is higher, support is both lower across the board and the effect of income steeper. Perhaps counter-intuitively, it appears that where immigration has been increasing the rich are significantly *more* supportive of redistribution.

Figure 4.11 can perhaps help make sense of this pattern. It shows the same interaction with the same hypothetical values but from a flipped perspective. By first

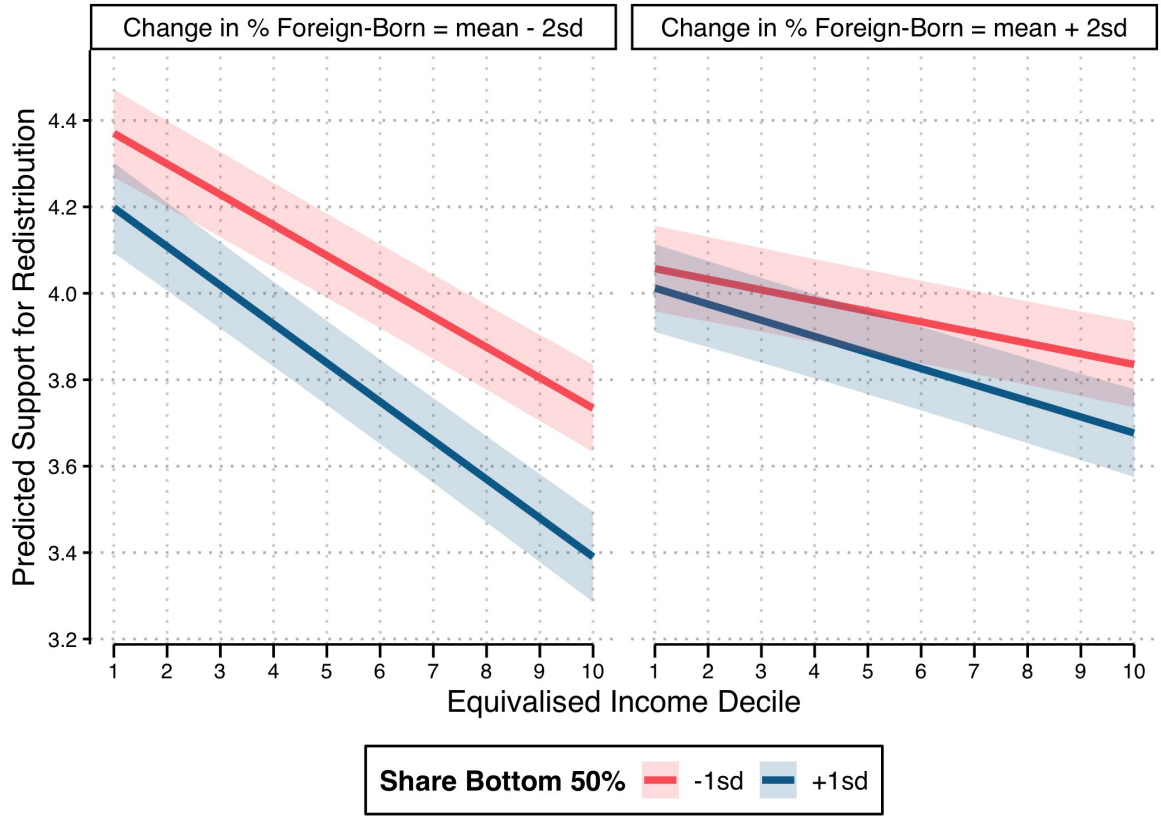


Figure 4.11: Predicted Outcomes with Three-Way Interaction II

Note: Point estimates based on model 10 with 90% confidence intervals.

conditioning on the values of changes in the share of foreign-born, it appears that now the pattern observed in Figure 4.9 - whereby the positive effect of inequality on support for redistribution is larger for the rich than the poor - is only discernible in a context of lower immigration. In contrast, the models do not predict any difference across incomes between high and low inequality contexts when immigration is high. Figure 4.12 provides another perspective on all these moving parts. It shows the coefficient of the change in % foreign-born depending on the income share of the bottom 50%, holding income decile constant at 0. It suggests that the effect of immigration on support for redistribution is stronger, negative and statistically significantly different from zero at lower shares of income of the bottom 50%.

As mentioned above, I also estimate the same models with a binary operationalisation of support for redistribution. The results thereof are shown in Appendix B.4. Additionally, I re-calculate the models in this section by, in one version, using the Palma ratio instead of the share of the bottom 50% and, in the other version, with medium term (i.e., 8-year) change in the share of % foreign-born. These results are shown in

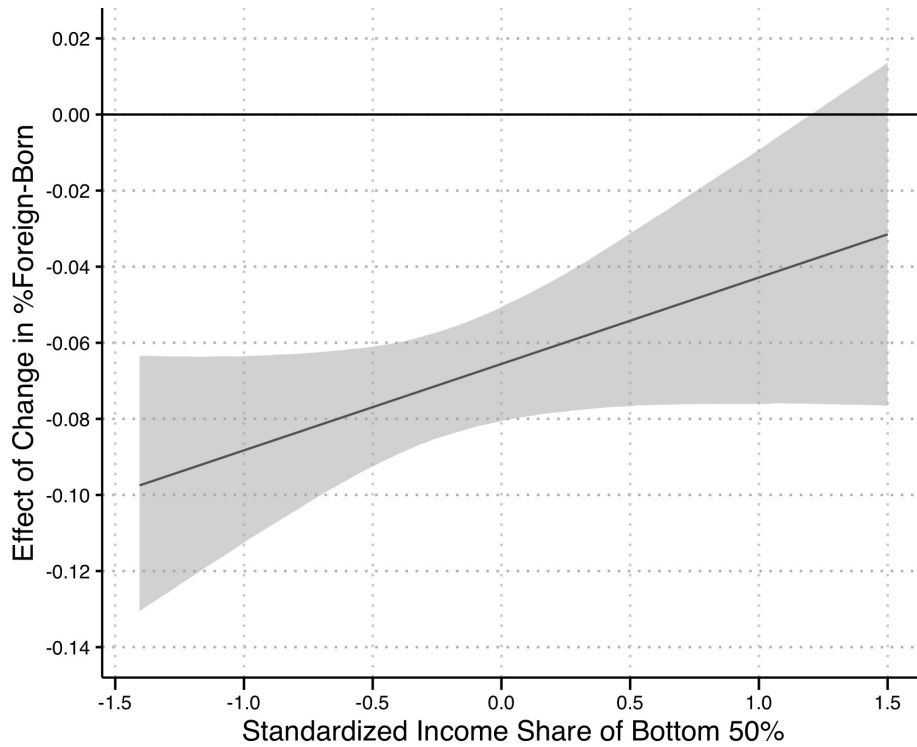


Figure 4.12: Effect of Immigration conditional on Inequality
Note: Point estimates based on model 10 with 90% confidence intervals.

Appendix B.5. To cut a long story short, these alternative specifications yield roughly similar patterns than the ones presented here. Two-way interactions between measures of immigration and income indicate a negative effect on support for redistribution more for the poor than the rich and two-way interactions between measures of inequality suggest a positive effect more for the rich than the poor. Moreover, the three-way interactions suggest that the interactive pattern between inequality and income is more apparent in a context of lower immigration; and that the interactive pattern between immigration and income is more apparent in a context of higher inequality driven by a lower share of income received by the bottom of the income distribution.

Finally, I also briefly investigate the effect of changes in different parts of the income distribution via the threshold ratios between the 50th and 10th and 90th and 50th respectively.³⁶ Figure 4.13 displays the predicted outcomes for a model where income is interacted with each ratio. Considering these two-way interactions, it appears that it is the ‘extension’ at the top that drives differences in support for redistribution and that it is the rich that become more supportive when the 90/50 ratio increases.

³⁶Note that all models also include a two-way interaction between the two ratios to account for their strong correlation.

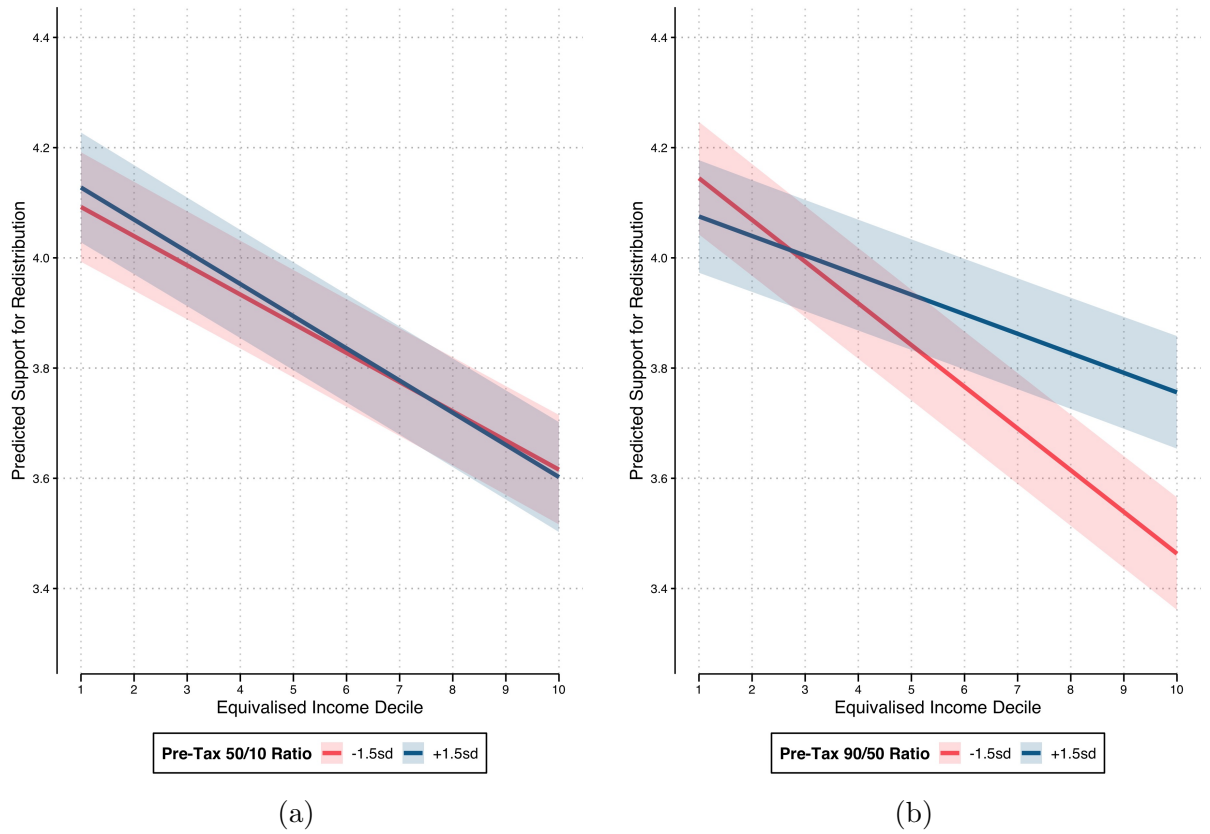
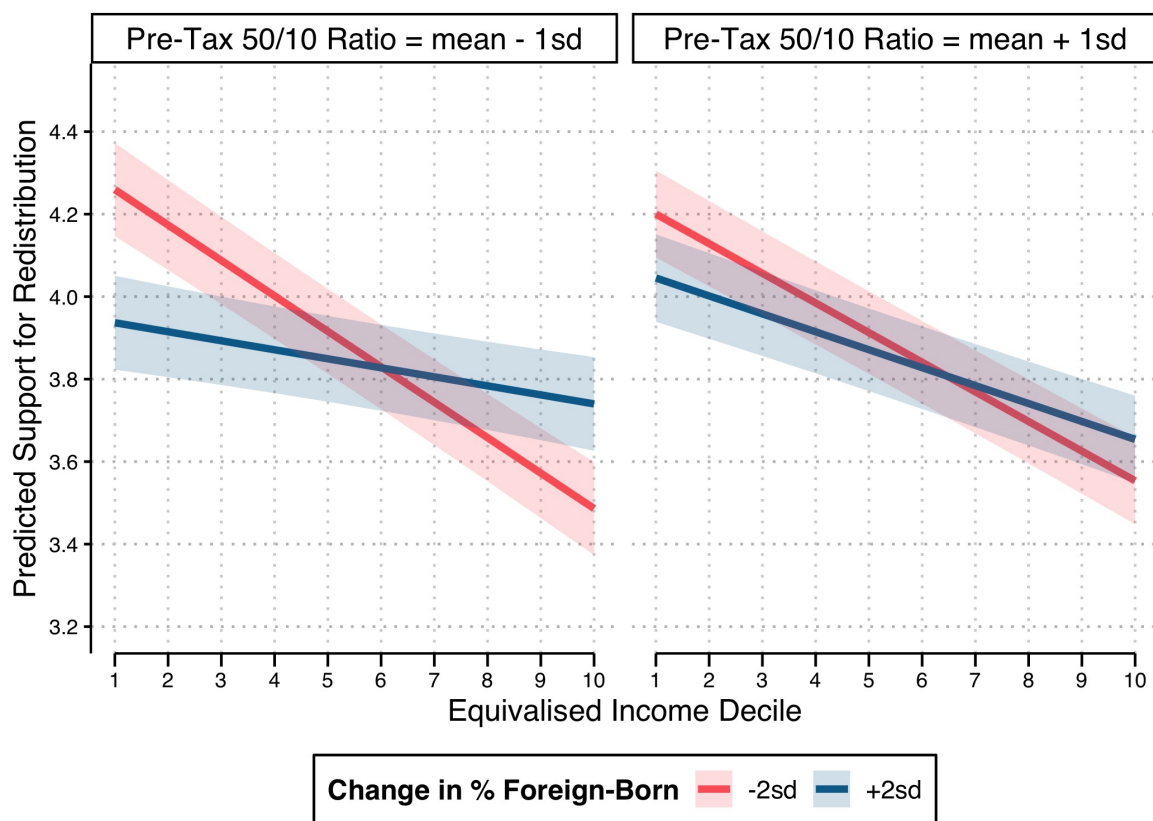
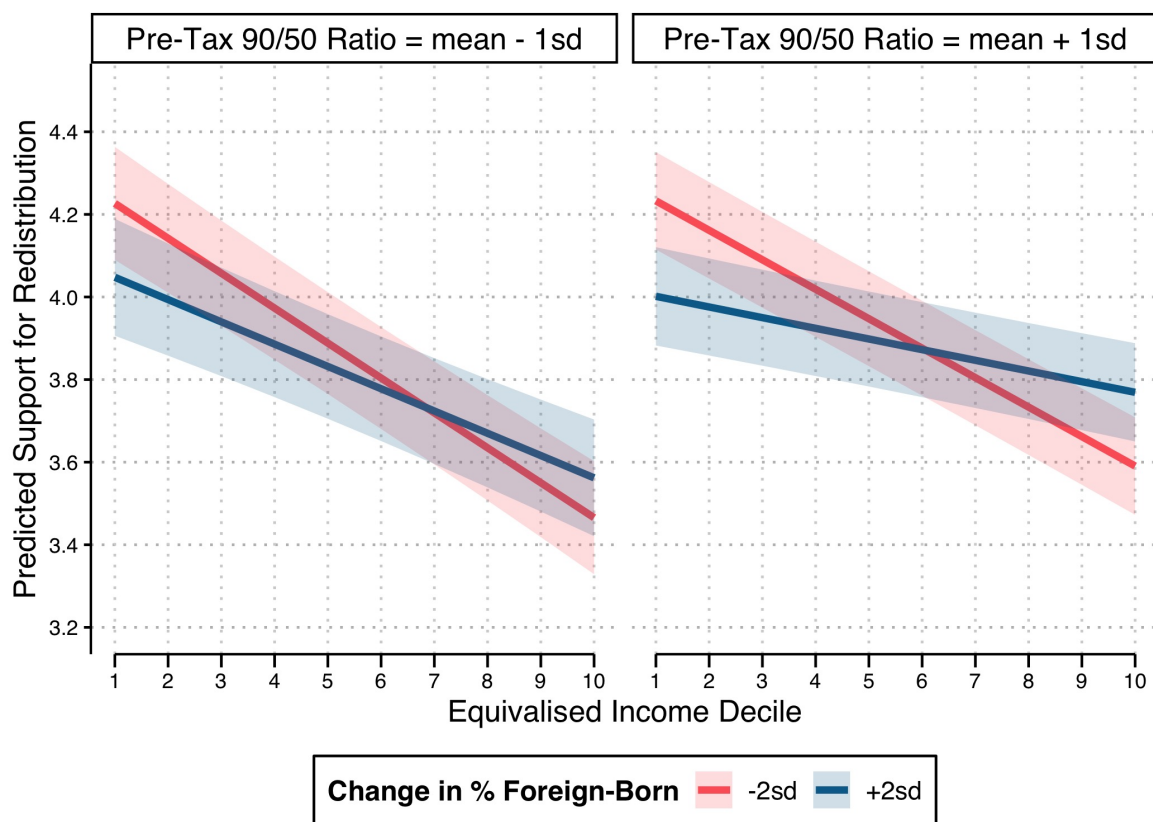


Figure 4.13: Interaction of Income with Income Ratios
Note: Point estimates based on model 7 in Appendix B.3 with 90% confidence intervals.

However, when interacted further with the measure of immigration, it is the 50/10 income threshold that appears more relevant. Indeed, as can be seen in Figure 4.14, when the ratio – i.e. the income distance between the 50th and 10th percentiles – is low (and holding the 90/50 threshold constant at its mean), the two lowest income deciles appear to be significantly less supportive *when immigration is high*. Conversely, the level of immigration does not appear to have an effect on how the 90/50 threshold moderates the relationship between income and support for redistribution.



(a)



(b)

Figure 4.14: Three-way of Income with Income Ratios and $\Delta\%$ Foreign-Born
Note: Point estimates based on model 10 in table B.3 with 90% confidence intervals.

4.5 Discussion & Conclusion

The analyses in this chapter aimed at investigating the level of support for redistribution of individuals depending on different levels of immigration and inequality at the macro-level. It goes without saying, that the kind of data used here does not allow me to make any credible inferences about the causal effect of the independent variables and their interactions on the dependent variable. Therefore, the goal of the analyses is descriptive inference - in other words: establishing whether there are any systematic associations between the variables, and whether these are congruent with the implications of the hypothesised mechanism. In the previous chapter, I argued that people oppose more income redistribution even if they stand to make absolute gains from it, if they perceive their relative income position, that is tied to their (perceived as deserved) social rank, to be under threat from below. This would have more traction with the poor than the rich, based on the logic that those already ranked lower will feel more competitive pressure by those ranked even lower than someone for whom the last place is further away. Additionally, I identify two contextual factors that are likely to activate this mechanism, resulting in lower aggregate support for redistribution: higher immigration and an income distribution that is more ‘compressed’ at the bottom.

In sum, if positional competition is a relevant driving factor for people’s preferred level of income redistribution, one should observe lower support for redistribution where the competition is fiercer and the competitors are more socio-culturally different. In the main analyses, I operationalised ‘fiercer’ (or tighter) competition as the share of pre-tax income received by the bottom 50% and how different the competitors are as the change in the share of foreign-born population over the four years leading up to, and inclusive of, the survey year. I operationalised individuals’ position in the income distribution as decile rank based on their household income equivalised by household size. I explored the interactive patterns between those three variables within survey data from the ESS and the ISSP spanning 20 years and 25 European countries. I used multiple imputation to curtail bias resulting from item-non-response. The models all included random effects to control for any systematic country-specific and year-specific differences.

The results of the multilevel regressions are broadly in line with the theoretical

expectations and robust to the inclusion of individual-level controls, macro-level controls, and alternative operationalisations of the main variables. Increases in the share of foreign-born people are associated with small but systematic decreases in average support for redistribution. Relevantly, this effect appears to be dependent on income. It is the lower deciles that are significantly less supportive of redistribution in high immigration compared to low immigration contexts. Even more, this income dependent effect of immigration appears to be amplified when the income share of the bottom 50% is lower (or the Palma-ratio higher).³⁷ Conversely and by itself, a lower share of national pre-tax income going to the bottom 50% is associated with higher support for redistribution, and more so for the rich than the poor. This is in line with arguments about the “altruistic rich” (Dimick et al., 2017), who are the ones who can ‘afford’ to care about the poor when inequality is high. Yet this is not necessarily in contradiction with the present argument and findings. In a theoretical level, one can extend the formal model presented in the previous chapter to accommodate *both* income dependent altruism and income dependent resentment, where the former matters more for the rich and the latter more for the poor.³⁸ Moreover, while support for redistribution is indeed higher in a high inequality context, and especially for the rich, it is relatively lower for the poor where immigration is also high (see figures 4.10, B.10 and B.13).

It is important to note, however, that the estimated effects and predicted differences in outcome are substantively quite small. Especially for immigration, the models suggest that relatively large differences in the independent variable are needed to elicit statistically and substantively significant difference.³⁹ More broadly, it is striking how little of the variance in these extremely widely used survey items the models are able to account for (how widely can be seen in Table 4.2). Even when including all the individual and upper-level controls that have been found to matter for redistributive preferences, the amount of so-called explained variance in the responses by the surveyed

³⁷It is worth adding here that the immigration measure has only a weakly positive correlation of 0.22 with share of the bottom 50% and a weakly negative correlation of -0.23 with the Palma-ratio.

³⁸This is shown and discussed in Appendix A.4. In fact, a model integrating both essentially would predict a shallower income effect, where the poor are less supportive than one would expect and the rich more - which is what can be observed in the right hand panel in Figure 4.11.

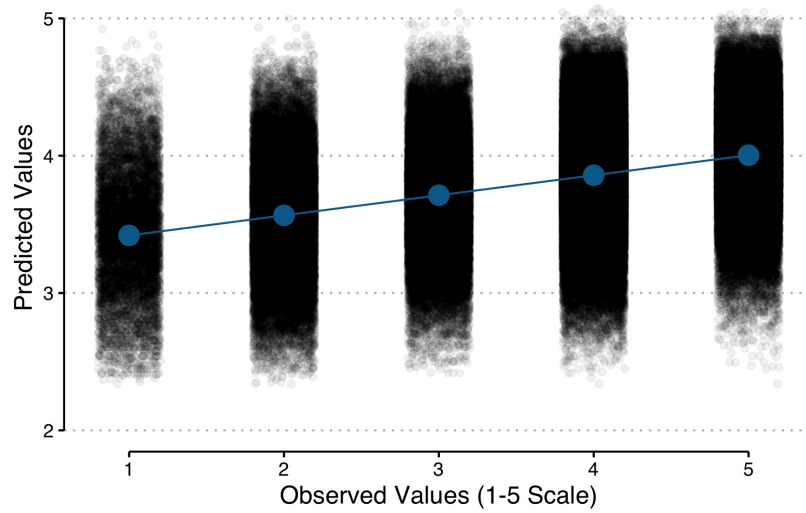
³⁹Note though, that when the medium term immigration variable is used, smaller changes are needed to yield similar differences.

individuals remains quite low.⁴⁰ Figure 4.15 illustrates this quite effectively by showing that the models seem to be ‘wrong’ about the expressed responses of the surveyed individuals quite a lot of the time. Even though the aim of these models is also not out-of-sample prediction and are therefore kept parsimonious, inferences about the meaningfulness of the observed patterns should still be done with caution. And yet, they should not be dismissed as trivial either. At the risk of borrowing an old and perhaps by now clichéd adage, “all models are wrong but some are useful” (Box, 1979).

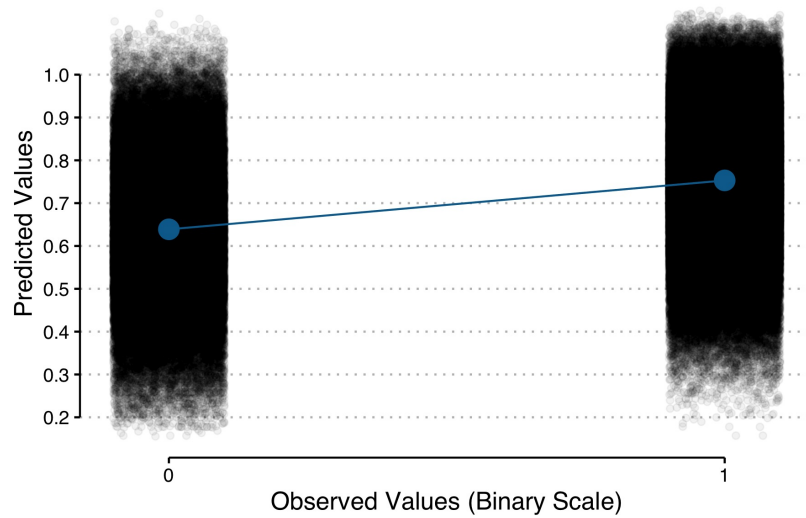
So, after all this, what can be said about these results? For one, it appears that the poor are less supportive of income redistribution in a context of higher recent immigration, and even more so in places where the poor do not receive a large share of pre-tax income. Why that is, these results cannot provide answers to. It remains an interesting, and possibly counter-intuitive, finding that where the poorer half of society is poorer, the poorer parts of society seem less willing to support redistribution when immigration has been high. This finding cannot be explained only by pure anti-solidarity effects, as, in this case, the level and structure of inequality would not matter and it would affect the rich and poor equally. It also cannot be explained by lack of altruism of the rich towards the poor when immigration is high, as, in that case, the differences in support for redistribution would be driven by the rich. The argument I put forward suggests that where the income distribution is already relatively compressed at the bottom, the poor care about preserving their relative position more. Then, when immigration and thereby the population share of an out-group perceived as having an inherently lower social rank increase, the poor will oppose more redistribution as this threatens to compress the income distribution even more. This arguably provides a better explanation for the observed patterns.

Taken together, the findings presented here call for further investigations into the interaction between the structure of inequality and immigration, and their consequences for public attitudes. However, there is a limit to which linear (or even generalised) multivariate regression models estimated on such time-series cross-country survey data can do. They are, by design, often constrained to assume linear, maybe additive, maybe polynomial effects and can only accommodate a limited amount of covariates

⁴⁰The results presented here are not the only ones in this case. The results in Jæger (2006), for instance, yield a likelihood given the model parameters for any given data point of about 0.22 to 0.27; the results in Guillaud (2013) have pseudo R^2 -s ranging from 0.055 to 0.087 and from 0.07 to 0.16 in Barnes (2015).



(a)



(b)

Figure 4.15: Predicted vs. Observed Values

Note: The predicted values were calculated with the most comprehensive model (model 12) on the original, non-imputed data, once with the 5-point and once with the binary dependent variable.

and interactions before they become too complex and impossible to interpret⁴¹ - and thus less useful. The task of unpacking the interdependent effects of all these moving parts can arguably be better handled by experimental designs, where the researcher has more control over the ‘moves’ of the independent variables. It remains that such observational evidence can tell us whether there are any systematic patterns to begin with that are worth exploring further - causally or otherwise.

⁴¹The three-way interaction was already (no) fun enough.

5.1 Introduction

As discussed in some length in the previous chapter, observational data can only go as far as to uncover patterns of *associations* between different variables such as individual preferences and macro-contexts. The question whether the two are causally linked cannot really be answered with this type of data. It is close to impossible to account for all the ways in which dependent, independent and control variables endogenously may affect each other. In those situations, it is up to the researcher to tell a compelling enough story about the causal mechanisms at work behind the scenes. Fortunately, the social scientist's toolbox includes other more creative and increasingly cost-effective ways to tackle the issue of causality with more precision. And yet, making it possible for the researcher to manipulate potentially relevant parameters in people's calculations will to some extent be at the expense of the scope and generalisability of the findings.

With this in mind, I conducted a survey experiment in May 2018 with YouGov. In this experiment, respondents were randomly allocated to four groups that were exposed to either none, one or both of two vignettes. Based on respondents' self reported gross household income, the first vignette informed them about the average income of those poorer than them before and after transfers as well as the share of the population these represent. This information is exactly the one with which I formalise my argument as seen in Chapter 3, on page 47. The second vignette contained a couple of sentences about the increase of immigration into the UK in the last decades. Two factual statistics were mentioned: namely, that more than half a million people arrived in the UK in

the preceding year; and that one out of seven UK residents was an immigrant – an increase of more than 50% compared to 2004. I measured support for redistribution on a 1-10 scale indicating support of the government raising taxes on all people to redistribute income more equally. I mainly use this as the dependent variable for the analyses. Additionally, I also asked respondents to specify their preferred tax rates for a) everyone (i.e. a flat tax) and b) for the bottom 60% and top 40%. However, the analyses with these as dependent variables do not yield any conclusive results. I discuss the possible reasons for this in section 5.4.4.

The results show that the respondents exposed to *both* vignettes combined became, on average, less supportive of income redistribution. Conversely, average support in those groups exposed to either one or the other is not statistically distinguishable from the control group. Substantively, the estimated effect size of the combined vignettes is similar to the effect associated with moving up four income categories. These results are robust to the use of different estimators and the inclusion of covariates. They are supportive of hypotheses 1 and 3 in the sense that it is the combination of a downwards comparison and priming of the increase of immigration that meaningfully affected redistributive preferences. There is also some tentative evidence for the presence of heterogeneous treatment effects dependent on income. Specifically, the negative treatment effect of the combined vignettes appears to be particularly large for the lowest income category, which is in line with hypothesis 2.

This chapter is structured as follows. In section 5.2, I first introduce the potential outcomes framework that can help structure how to think about causality and why experiments help us overcome selection bias. I also briefly discuss the intuition behind survey experiments in general before summarising the theoretical intuition behind the survey experiment that was conducted. In section 5.3, I explain the design of the experiment, detailing the treatments and how the dependent variable is measured, as well as relevant covariates. In section 5.4, I present the results of the experiment before discussing their implications in light of the theoretical argument in section 5.5. I conclude in section 5.6.

5.2 The (Survey) Experimental Logic

5.2.1 The Potential Outcomes Framework

In an ideal world, the universe would be a multiverse, where we could observe two versions of reality at once; one where something of interest to the researcher occurred and one when where it did not occur. If that were possible, it would be straightforward to deduce what the causal effect of that something was by comparing fact and counterfactual. This is the core idea behind the “Potential Outcomes Framework” which mainly goes back to the work of Rubin (1974, 1977) and Holland (1986), based on the ideas set out by Neyman (1923) and Fisher (1925). Adopting the notation of Angrist and Pischke (2009) and with treatment being described by a binary random variable $D_i = \{0, 1\}$, the potential outcomes in Y_i of for unit i can be described as:

$$Y_{di} = \begin{cases} Y_{1i} & \text{Potential outcome for unit } i \text{ with treatment} \\ Y_{0i} & \text{Potential outcome for unit } i \text{ without treatment} \end{cases} \quad (5.1)$$

Following from this, the average treatment effect (ATE) across a population of units i of the treatment on the outcome is defined as the expected value of the difference between their two potential outcomes:

$$\tau_{ATE} \equiv E[Y_{1i} - Y_{0i}] \quad (5.2)$$

Therefore, if we could observe parallel universes, where all is equal except that treatment is applied to all i 's in one version of reality, and not in the other, we could easily calculate the average causal effect of D . However this is, quite obviously, impossible. This is the *Fundamental Problem of Causal Inference* (Holland, 1986, 947). At the root of causal analysis lies, first, the acknowledgement of the Fundamental Problem of Causal Inference and, second, the overcoming of the Fundamental Problem of Causal Inference by developing robust methods which can inform us about what the counterfactual may plausibly be.

5.2.2 Selection Bias and Randomization

The naive approach would be simply to find observations with different treatment status and use the difference in the mean outcome by treatment group. However, such an approach is likely to provide a biased estimate of the treatment effect as the potential outcomes may not be independent from treatment status. In simple words, this means that it is difficult to rule out that the units about which we want to make inferences did in fact select into (or out of) treatment, making observations in one group poor approximations of the counterfactual for the observations in the other, and vice-versa. This is commonly referred to as *selection bias*.

The general approach to account for selection bias is to neutralise potential sources of confounding¹ by controlling for them either via modelling specification or by design. The design-based approaches usually produce more credible estimates of causal quantities, as, if successfully implementable, they control for both observable *and* unobservable confounders. In this context, randomized experiments are, in the words of Holland (1986, 946) not “the *only* proper setting for discussing causality, but [they are] the *simplest* such setting.” The intuition is that, by randomly assigning units into treatment and control, selection into treatment and control will be independent of confounders and therefore of potential outcomes. As Angrist and Pischke (2009, 16) put it, “[r]andom assignment works not by eliminating individual differences but rather by ensuring that the mix of individuals being compared is the same.”

The identification assumption needed to make causal inference possible is that treated and untreated potential outcomes are independent of treatment assignment.

$$(Y_1, Y_0) \perp\!\!\!\perp D \quad (\text{random assignment}) \quad (5.3)$$

If this assumption holds, the expected value of the observed outcomes for the treatment group will be an unbiased estimator of the expected value of the treated potential outcomes, and the expected value of the observed outcomes for the control group will

¹Confounding and selection bias essentially mean the same.

be an unbiased estimator of the expected value of the untreated potential outcomes.

$$E[Y_i|D_i = 1] = E[Y_{1i}] \quad (5.4)$$

$$E[Y_i|D_i = 0] = E[Y_{0i}] \quad (5.5)$$

From this follows that, under random assignment, the difference in means between treatment and control group will be an unbiased estimator of the average treatment effect.

$$\tau_{ATE} = E[Y_i|D_i = 1] - E[Y_i|D_i = 0] \quad (\text{estimand}) \quad (5.6)$$

$$\hat{\tau}_{ATE} = \frac{1}{N_1} \sum_{D_i=1} Y_i - \frac{1}{N_0} \sum_{D_i=0} Y_i \quad (\text{estimate}) \quad (5.7)$$

5.2.3 Experiments within Surveys

Survey experiments combine representative samples and randomized assignment – surely a combination that makes for rigorous science. [...]

These three limitations of survey experiments – modesty of treatment, modesty of scale, and modesty of measurement – need constantly to be borne in mind when brandishing the term experiment as a prestige enhancer.

– Sniderman (2018, 260)

In many areas of research, randomisation of treatment assignment happens rarely ‘in the real world’. From social scientists’ perspective, it is often difficult to achieve and sometimes unethical. In contrast, ‘laboratory’ experiments allow the researcher to fully control the specifics of the study and therefore make a precise isolation of causal effects possible, ensuring internal validity. However, such experiments often are conducted on unrepresentative samples (e.g. university undergraduates), or may suffer from unrepresentative treatments. Therefore, conclusions reached about an estimated treatment effect from a laboratory experiment may not be very informative about what would happen if implemented ‘in the real world.’ This is arguably of particular relevance in the social sciences where the object of research is behaviour or attitudes of individuals or social entities, and not, for instance, viral cells that are probably not aware that they are being studied in a lab. Therefore, strictly speaking, experiments allow in first

instance to recover the *Sample* Average Treatment Effect (SATE). Whether this is also an unbiased estimated of the *Population* Average Treatment Effect (PATE) depends on the degree of representativeness of the sample.

Survey experiments present some solution to this challenge of external validity by combining randomisation of treatment assignment in the context of larger surveys that are, ideally, representative of the population of interest (Mutz, 2011; Krupnikov and Findley, 2016, 488).² Experiments conducted within surveys all involve a random (and more or less complex) manipulation of how and with what kind of framing the survey question is posed to respondents.³ Contrary to laboratory experiments, where the *behaviour* of participants can be observed, survey experiments tend to be more informative about the possibly different *attitudes* a particular treatment would elicit.⁴

Conducting and reporting the results of survey experiments should therefore be accompanied by modesty (Sniderman, 2018). Experimental manipulation in surveys, especially when limited to variations of information treatments, has often been described as weak (Mutz, 2021, 221). More often than not, what can hope to be observed is a small, and possibly only short-lived differences in the outcome variables of interest; in part due to cost-concerns and limitations on the complexity of treatment that can reasonably be put to survey respondents.

Nonetheless, even if weak, it is still worthwhile investigating whether a particular treatment affects (or does not affect) someone’s attitudes and behaviour that are relevant to social, political or economic life. Moreover, any empirical approach necessarily has their advantages and disadvantages, their own particular trade-offs that the researcher needs to consider when designing as well as reporting a study. In what follows, I seek to follow Sniderman’s advice of modesty.

5.2.4 This Survey Experiment’s Logic

The mechanism underpinning the theoretical argument of this thesis is based on the idea that people’s support for redistribution is also dependent on an “individual’s relative

²Or, at least, more representative than the usual type of participants in lab-experiments.

³For instance, by varying the wording of the question (Question Wording Designs), by varying the kind of information provided just before the question (Vignette Experiments), or by varying the options among which respondents have to choose (Conjoint Experiments).

⁴Although there have been some important developments in that respect. See for instance Peterson et al. (2021).

position along these [material] dimensions [to] a given reference group” (Kuziemko et al., 2014, 105). I assume that people care about their *relative* material position, and in particular towards those poorer, as it acts as a signal for their place in the social hierarchy which they seek to preserve. If this assumption holds, differences in incomes observed through downwards comparisons can appear justified and, I argue, curb people’s preferred level of redistribution, especially in a context of cultural heterogeneity.

The expectation of the theory is that respondents will feel more negatively about their relative position when aware of the increase in immigration. They want to distance themselves from those poorer than them, and become less supportive of redistribution and its compressing effect on the income distribution. Therefore, the present experiment tests whether respondents’ level of support for redistributive measures changes when confronted with information about their relative position towards the poor in the income distribution (before and after benefits) in conjunction with information about increasing immigration. It is designed to reproduce elements of political discourse that combines the triggers such as ‘Look at how you are doing compared to people poorer than you’ and ‘Look at how immigration has increased.’

Moreover, I hypothesise that the effect is not the same depending on income. As the status struggle is a struggle for distinction from others, those with fewer people below them are the ones that have the most to lose in terms of relative status from a compression of the income distribution. Therefore, I will also estimate the *conditional average treatment effect* (CATE), which is defined as follows:

$$\tau_{CATE} = E[Y_i|D_i = 1, X_i = x] - E[Y_i|D_i = 0|X_i = x] \quad (5.8)$$

where X_i is the income category of i (c.f. Ratkovic, 2021).

5.3 Experimental Design

Thanks to the Oxford Department of Politics and International Relations’ collaboration with the UniOM programme from YouGov, I could conduct an experiment testing the mechanism of the argument. The survey experiment was fielded online on the 2nd of May 2019 as part of YouGov’s standard political omnibus survey. Out of the 1813 respondents, 371 did not provide an answer when asked about their household income.

As a non-missing response to the income question is essential, this leaves me with 1442 respondents overall (including those who might not have wanted to answer to the post treatment question).⁵ The randomly divided survey groups are structured as displayed in Table 5.1.

Table 5.1: Survey groups - YouGov experiment

	No information about inequality	Relative Inequality
No information about immigration	C 340 obs.	T1 362 obs.
Information about immigration	T2 385 obs.	T3 355 obs.

C= Control, T= Treatment

Each cell corresponds to a group being exposed to random variation of vignette combinations with information about recent trends in immigration and information about the income distribution below the individual position. These vignettes are listed below and can be seen as they were shown to respondents in Figure 5.1.

Treatments

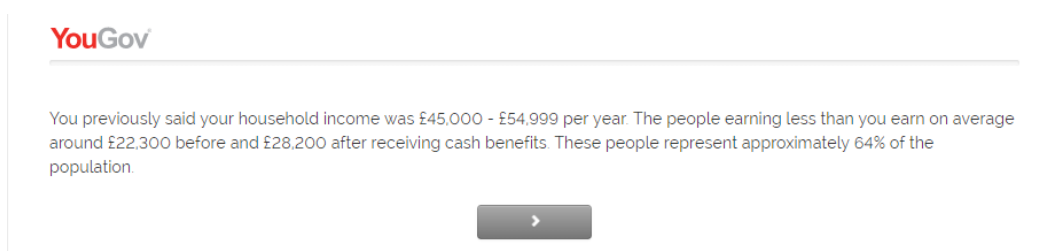
C No vignette

T2 You previously said your household income was _____. Before receiving cash benefits or paying tax, the people who earn less than you earn on average around _____. After receiving cash benefits (but still before paying tax), these same people earn on average _____. These people represent approximately ____% of the population.

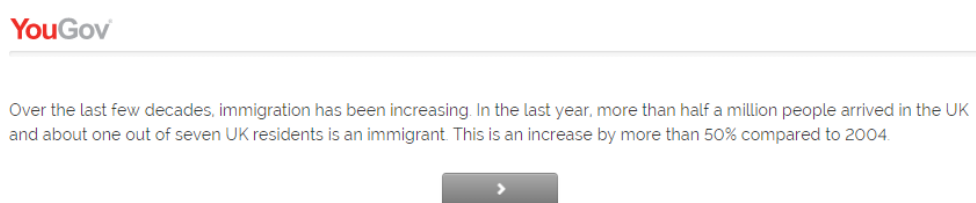
T3 Over the last few decades, immigration has been increasing. In the last year, more than half a million people arrived in the UK and about one out of seven UK residents is an immigrant. This is an increase by more than 50% compared to 2004.

⁵It is worth keeping in mind that low-income people tend to have higher rates of non-response, meaning that they are likely under-represented in the working sample. However, this is less of a concern than item non-response *after* treatment, as this would introduce post-treatment bias into the estimates. I expand on this below.

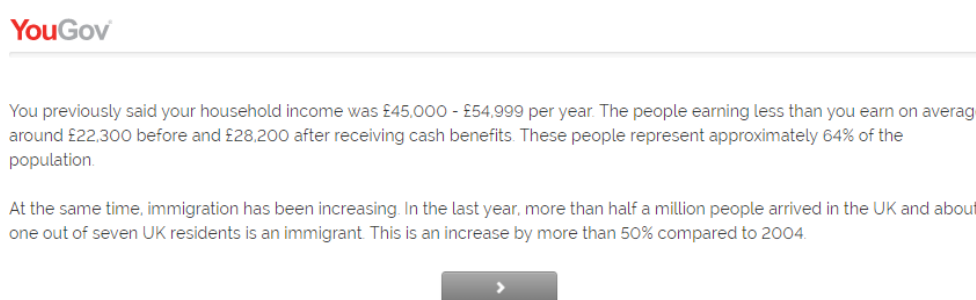
$T4 = T2 + T3$ - You previously said your household income was _____. Before receiving cash benefits or paying tax, the people who earn less than you earn on average around _____. After receiving cash benefits (but still before paying tax), these same people earn on average _____. These people represent approximately ____% of the population. At the same time, immigration has been increasing. In the last year, more than half a million people arrived in the UK and about one out of seven UK residents is an immigrant. This is an increase by more than 50% compared to 2004.



(a) T2



(b) T3



(c) T4

Figure 5.1: Vignettes

The vignette for T2 is quite self-explanatory. The one providing information about the income distribution below requires more explanation. Unfortunately, in order to maximise the response rate, opinion surveys generally rely on income bands to measure (household) income as opposed to more precise numeric inputs. Therefore, YouGov asks people to indicate their gross household income by choosing among the categories

Table 5.2: Income Figures used for the Micro-Inequality Vignette

Income bands	Midpoint	Pre-transfers		Post-transfers
		Percentage below midpoint	Ave. income below midpoint	Ave. income below midpoint
Under £10,000	£6,667	14%	£2,500	£4,500
£10,000 to £14,999	£12,500	21%	£4,900	£9,000
£15,000 to £24,999	£20,000	30%	£8,400	£13,700
£25,000 to £34,999	£30,000	42%	£13,200	£19,400
£35,000 to £44,999	£40,000	54%	£18,100	£24,300
£45,000 to £54,999	£50,000	64%	£22,300	£28,200
£55,000 to £69,999	£62,500	75%	£27,300	£32,200
£70,000 to 89,999	£80,000	85%	£32,400	£37,100
Over £90,000	£141,197	96%	£38,300	£42,500

Note: All of these numbers are pre-tax.

displayed in the first column of Table 5.2.

In order to calculate the income distribution below each category, I rely on the Luxembourg Income Study (LIS) which pools detailed information about many countries' income distributions and tax system. For the UK, the LIS uses the Family Expenditure Survey and the latest available data is from the fiscal year 2016/2017. I calculated the income for each percentile in the distribution for both pre-transfer and post-transfers gross income. Based on this data, I created a function able to calculate the average income and the proportion of people poorer than any given income.⁶

I then calculate average income and share relative to the midpoints for each income band. For the top and bottom categories, I follow the recommendation from Hout (2004) to calculate a meaningful midpoint.⁷ This is summarised in Table 5.2.

Depending on which income band the respondents placed themselves, the corresponding information was then plugged into vignette 1/2 to constitute the treatment.

Post-treatment questions

After exposure to the vignettes, I asked three post treatment questions to measure preferences around redistribution. The first and main question of interest emphasises the link between taxes and redistribution and their role in reducing inequality of incomes.

⁶For illustration and to see this in practice, I have created an application that can be visited at <https://julia-derom.shinyapps.io/relSim/>.

⁷This technique uses the relative frequency of people in the second to top/bottom and top/bottom category to approximate the how the distribution looks in the tails. This yields more practical midpoints.

This is in contrast to many survey items used to measure support for redistribution in large (cross-)national surveys (some of which are shown in Table 4.2 in Chapter 4) that often only highlight one of the facets of redistribution – the “*redistribution to the poor*” (Cavaillé and Trump, 2015, 147).

The two next questions ask people to set their preferred tax rate if there was only one or two tax rates. They serve as complement to the first question (which framed taxes as a means for redistribution). How this looked like in the experiment is shown in Figure C.1.

- To reduce income differences between the rich and the poor, the government can raise taxes on all people in the UK to then redistribute income more equally among everyone. Please indicate below how supportive you are of such measures.
Sliding scale of 0 to 10 from “Not at all supportive” – “Very supportive”
- Imagine everyone was taxed at the same rate. What tax rate would you set?
Slider from 0 to 100%
- Now imagine there were only two tax rates, one for the bottom 60% and one for the top 40%. What tax rate would you set for each group?
Two sliding scales from 0 to 100%

Pre-treatment controls

Incorporating additional confounders in the analyses of experiments can be helpful to get a sense of whether randomisation has been successful (via balance checks) and to possibly increase the precision of the estimates (Angrist and Pischke, 2015, 95-97). Therefore, and in addition to household income recoded into midpoints as described above, I rely on a number of socio-economic indicators listed and described in Table 5.3, along with the distribution of the sampling weights provided by YouGov. All variables were measured before treatment. Below I use all variables except “lives with partner” to check balance and as controls. “Lives with partner” is used to equalise household income when analysing the results for heterogeneous treatment effects.

Table 5.3: Controls

(a) Continuous Variables

variable	min	median	max	mean	sd
Age	18.00	48.00	88.00	48.00	16.00
Income	5000	30000	113300	38900	27500
Weight	0.31	0.87	5.01	0.99	0.46

(b) Categorical Variables

variable (cat.)	levels	n	frequency
Gender	man	653	45.3%
	woman	789	54.7%
Living area	urban	1119	77.6%
	rural	323	22.4%
University degree	no	781	54.2%
	yes	661	45.8%
Employment status	not employed	229	15.9%
	retired	305	21.2%
	fulltime	648	44.9%
	parttime	260	18%
Social grade	DE	288	20%
	AB	435	30.2%
	C1	435	30.2%
	C2	284	19.7%
Political orientation	left	484	33.6%
	centre	258	17.9%
	right	377	26.1%
	don't know	323	22.4%
Lives with partner	No	554	38.4%
	Yes	888	61.6%

5.4 Results

5.4.1 Attrition and Randomisation Checks

Before analysing the experiment in light of the motivating hypothesis, it is crucial to see whether there may be any threats to internal validity, which would therefore result in biased estimates. Broadly, two ways in which internal validity can be compromised within an experimental design and which can also be, to some extent, investigated, are non-random attrition and failures of randomisation.

Non-random attrition refers to situations in which some units having missing outcomes is correlated with treatment assignment *and* with their potential outcomes

(Martel García, 2013). Therefore, removing observations based on their post-treatment missingness may introduce bias because of the underlying differences between those without missingness and those with. Importantly, while it is possible to test whether missingness is correlated to treatment assignment, it is not possible to test for the more problematic correlation between the rate of missingness and the unobserved potential outcomes.

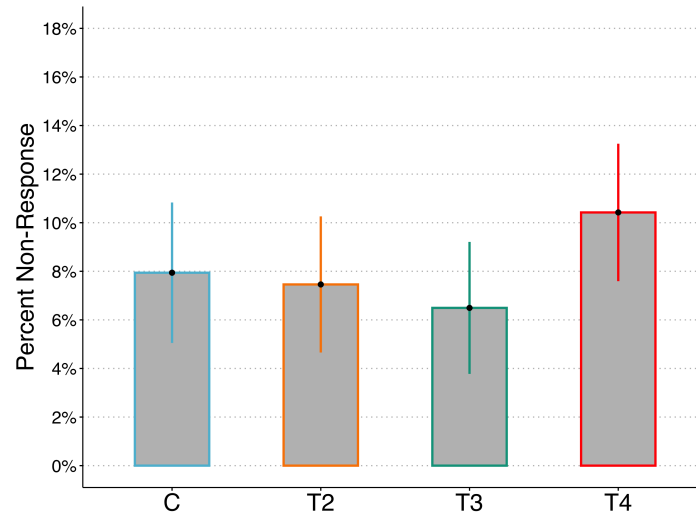


Figure 5.2: Attrition in the Dependent Variable
Vertical lines represent 95% confidence intervals estimated by regressing non-response to the main outcome variable on the treatment group indicators.

Figure 5.2 shows the proportion of missing values in the main dependent variable by treatment group. In the control group, the non-response rate is about 8%, followed by treatment group 2 with 7.5% and treatment group 3 with 6.5%. The rate of missingness among respondents who were shown both vignettes about their relative position and about recent increases in immigration is close to 10.4%. While the differences amongst these rates are not statistically significant, as can be seen by the overlapping confidence intervals in Figure 5.2, this notable higher attrition in the treatment group of interest may be cause for worry.

In order to limit the post-treatment bias introduced by this, I follow two strategies to strengthen the robustness of the results. First, I estimate the average treatment effects on an alternative specification of the dependent variable. Instead of using the full 0-10 range, I also create a binary version where all values above 5 are coded as 1 and 0 otherwise (including if missing). The distributions by treatment group are shown

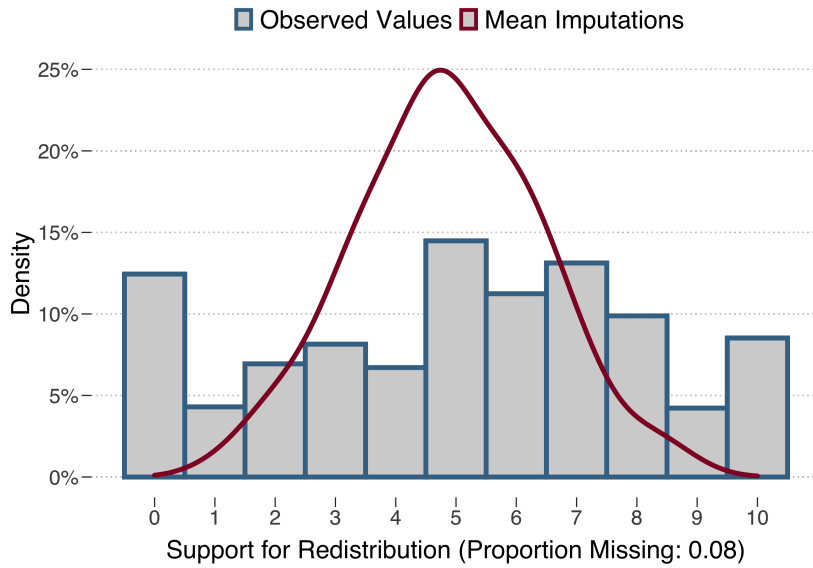


Figure 5.3: Imputations of Dependent Variable

for both the continuous and binary versions in Table C.1.

Second, I perform multiple imputation on the data following the method developed by King et al. (2001; see also: Blackwell et al., 2017). Contrary to the observational survey data used in the last chapter, the data is limited to the outcome variables. I use the pre-treatment covariates listed in Table 5.3 as well as the treatment indicators to impute the most likely outcome values for those missings with the `amelia` algorithm. Again in contrast to the observational survey data, the total number of observations is much smaller, meaning that the variance of the samples risks being too large. I therefore create 500 multiply imputed datasets, as opposed to only 5. The result of this process is shown in Figure 5.3, where the blue and grey bars show the observed distribution of the main dependent variable, while the red line shows the average imputation across all five hundred imputations.

Another potential source of estimation bias and therefore of threat to causal inference is failure of randomisation. Particularly in this case, where the sample was split into four, it may be that, by chance⁸, the random assignment did not ensure that “the mix of individuals being compared is the same” (Angrist and Pischke, 2009, 16). This would be a violation of the identification assumption shown on page 98. This is partially testable by assessing whether the empirical distribution of the *observable* covariates in the treatment group mirrors that in the control group.

⁸Or rather bad luck.

There is a certain amount of debate in the literature regarding which kind of statistical test is most appropriate.⁹ One possible avenue is by regressing the log odds of being in a particular experiment group on the available covariates Imai (2005). This is shown in Figure 5.4, where I estimated the effect of the covariates on selection into treatment via logistic regression. As there are three different treatments, I performed pairwise comparisons between each treatment group and the rest of the sample separately.

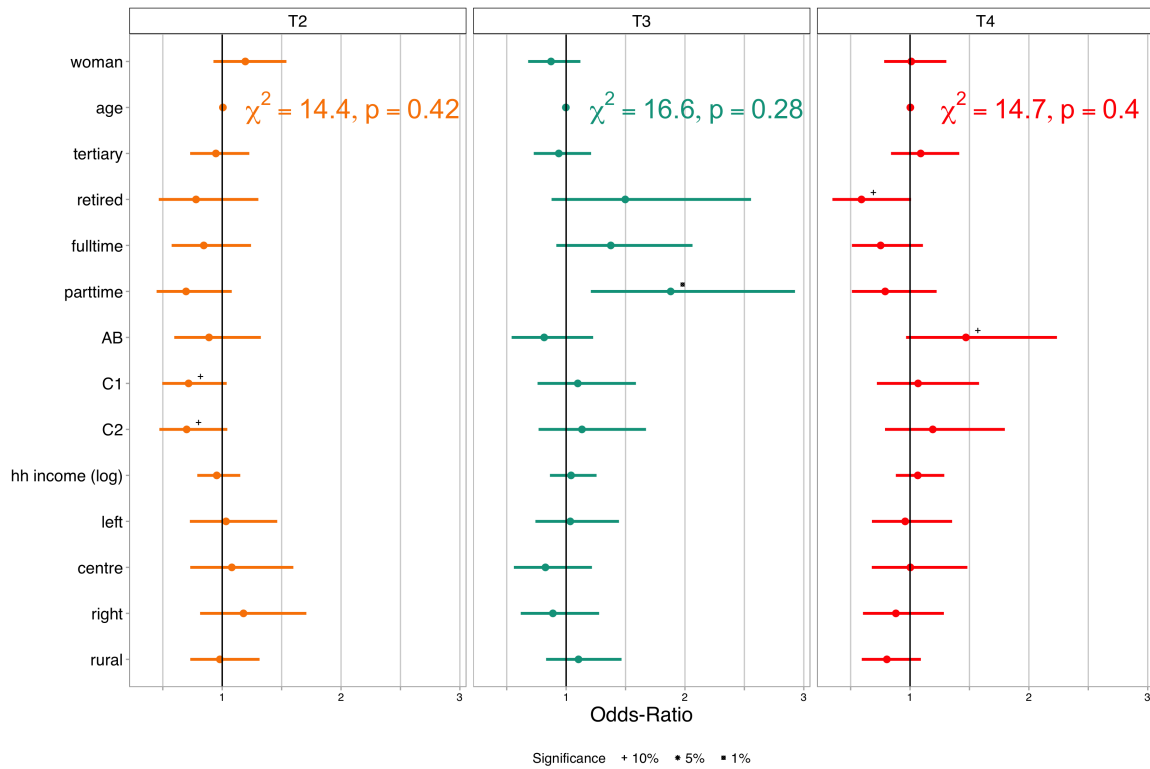


Figure 5.4: Balance Check via Logistic Regression
Odds-ratio coefficients estimated via three separate logistic regressions with, as a dependent variable, 1 if assigned to treatment groups T2, T3 and T4 respectively, 0 otherwise.

The coefficients of each covariate are expressed as odds-ratios, which can be interpreted as the value by which the probability of $Y = 1$ (in this case: being assigned to treatment) is multiplied for each one-unit increase of X . As seen in Figure 5.4, it seems that people with social grade C1 and C2 were respectively 0.3 times less likely to be in treatment group 2 than social grade DE. Moreover, people working part-time were 0.9 times more likely to be in treatment group 3 than unemployed and not employed people. Moreover, retirees appear to have been 0.6 times as likely than unemployed

⁹See footnote 5 on page 28 in Hainmueller (2012). In fact, Imai et al. (2008, 498) argue that “researchers analysing data from randomized experiments that did not block on all observed covariates can check balance, but they do not need hypothesis tests to do so.”

people, and people with social grade AB 0.5 times more likely than social grade DE to be assigned to treatment group 4. All other coefficients are not statistically significant neither at the 95 nor the 90% confidence level. Additionally, none of the models are overall statistically significantly better at explaining variation in treatment assignment than the null-model, according the likelihood-ratio tests whose results are displayed in the top right corners of each panel.

However, Hansen and Bowers (2008) criticise the use of logistic regression as a tool for balance check on the grounds of the stringent sample size requirements to yield valid p-values. They show, based on the well-known get-out-the-vote experiment from Gerber and Green (2000), that p-values from logistic regression will tend to be too small on subsamples and be “prone to spuriously indicate lack of balance when there are too many covariates relative to observations” (Hansen and Bowers, 2008, 14). Instead, they advocate for the use of Fisher’s randomisation test, which tests whether differences between groups *in the sample* can be explained by chance, rather than whether differences between sample and population can be explained by chance,

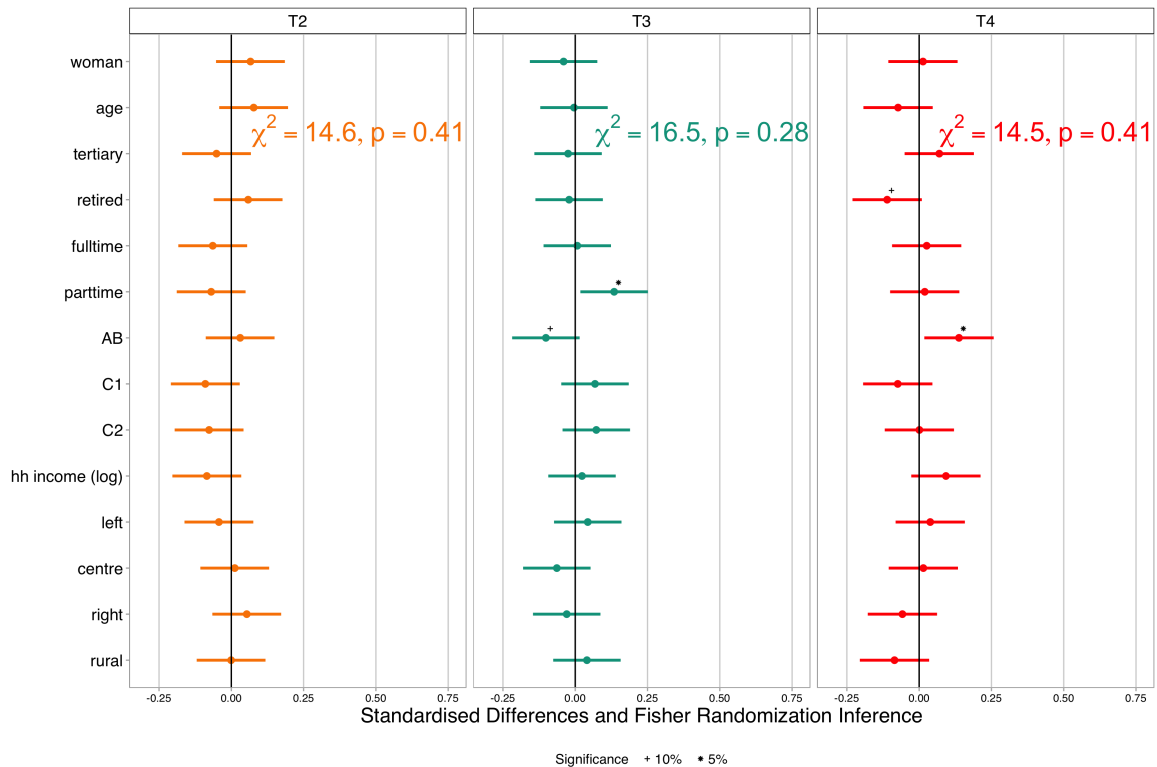


Figure 5.5: Balance Check via Fisher’s Randomisation Inference
Standardised differences in group means with 95% confidence intervals estimated via randomisation inference with with, as group identifier, 1 if assigned to treatment groups T2, T3 and T4 respectively, 0 otherwise.

which is what an omnibus test with logistic regression does. In contrast, randomisation inference generate test statistics and p-values by simulating every possible random assignment and then calculating how likely it would be to have observed the standardised differences in means between treatment and control group were they due to chance.

This is shown in Figure 5.5 which displays a very similar picture in terms of potential variables of concern than the logistic regression based balance checks. There appear to be slightly slightly more people working part-time in treatment group three, as well as slightly fewer people from the upper middle and middle class (social grade AB) in treatment group 3. Conversely, there seem to be slightly more upper middle and middle class respondents, as well as slightly fewer retirees in treatment group 4. However, the χ^2 -tests of conditional independence are close to the likelihood ratio tests obtained above and all statistically insignificant.

Both these two approaches do paint a similar picture in the end: while there appears to be a slight lack of balance with respect to some few specific covariates, neither test indicates that differences across treatment groups are sufficiently systematic to challenge the identifying assumption that, in expectation, the potential outcomes are the same across treatment groups. These are encouraging results regarding how (un)likely it is that randomisation failed in this case. Nonetheless, as a further robustness check, I also perform an analysis where I relax the assumption of random assignment (i.e. unconditional independence assumption). Instead, I estimate the ATE based on the *conditional* independence assumption, which states that the potential outcomes are independent of treatment, conditional on covariates X .

$$(Y_1, Y_0) \perp\!\!\!\perp D | X \quad (\text{conditional independence}) \quad (5.9)$$

Another identifying assumption is needed for such a selection on observables design, namely that the probability of treatment for each combination of relevant X 's need not be zero or one.

$$0 < \Pr(D = 1|X) < 1 \text{ for all } X \quad (\text{common support}) \quad (5.10)$$

Plainly, this means that I also estimate the ATE while controlling for suspected, observable, confounders with multivariate regression as well as with matching.

5.4.2 Average Treatment Effects

The quantity of interest is the effect on support for redistribution of being confronted with information about one's position in the income distribution relative to the poor **combined with** information priming respondents about the increase in immigration. Therefore, the focus lies on the third treatment vignette (T4). Figure 5.6 displays the empirical distribution of the main, continuous, outcome variable across the four groups in the form of boxplots. Their respective means and 95% confidence intervals are shown in black. Average support among the control group was 5.38, 5.12 in treatment group T2 (where only information about relative income position was shown), 5.08 in treatment group T3 (where only information about increased immigration was shown) and, finally, 4.55 in treatment group T4, which combined both vignettes. A cursory glance at the distributions within each treatment group suggests that this difference is not driven by only a couple of outliers, but the slight shift appears to be systematic across the range of the scale.

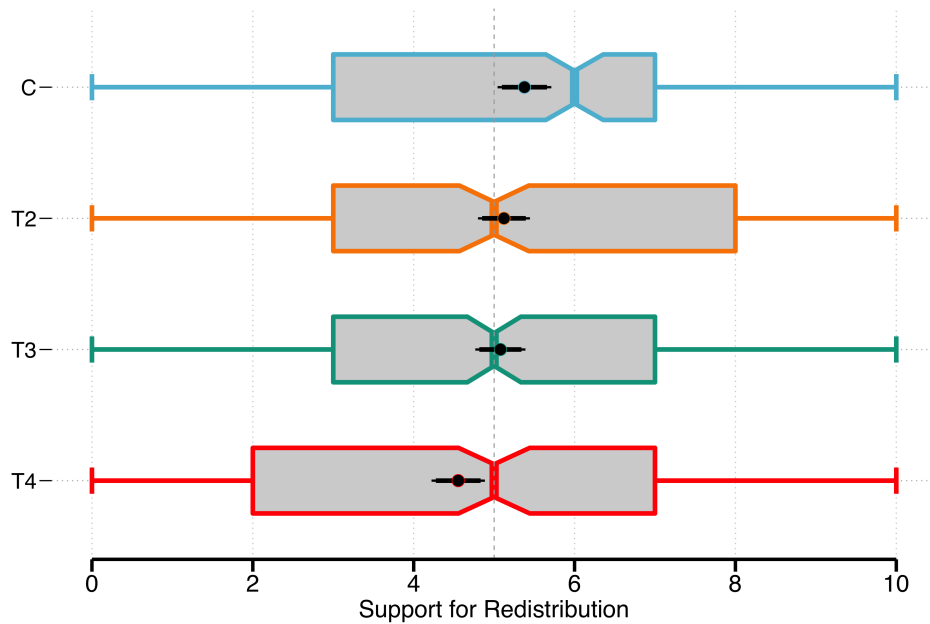


Figure 5.6: Distribution of outcome variable by treatment group

Regression Estimator

This is supported by the results obtained with linear regression, as shown in Figure 5.7. The left-hand panel displays the estimated coefficients (i.e. difference in group means) associated with each treatment group relative to the control group. Only T4 appears

to have had a statistically significant and negative effect, shifting average support for redistribution by about 0.8 points downwards on the 0-10 response scale compared to the treatment group.

This result is robust to the inclusion of covariates, as can be seen in the right-hand panel of Figure 5.7. In fact, the absolute size of the estimated SATEs increases slightly, with a coefficient for T4 of nearly -0.9 . The same figure also includes the coefficient associated with income as a benchmark to get a sense of the substantive significance of the estimated treatment effect. Here, income is a continuous variable ranging from 1-9, reflecting the 9 household income categories as they are described in Table 5.2. As such, multivariate regression predicts a 0.17 point decrease in support for redistribution for a one income-category increase. In comparison, the negative effect of treatment vignette T4 is akin to moving up five income categories (out of a total of 9). The same conclusions can be drawn from estimating the same models on the 500 multiply imputed datasets (see Figure C.2).

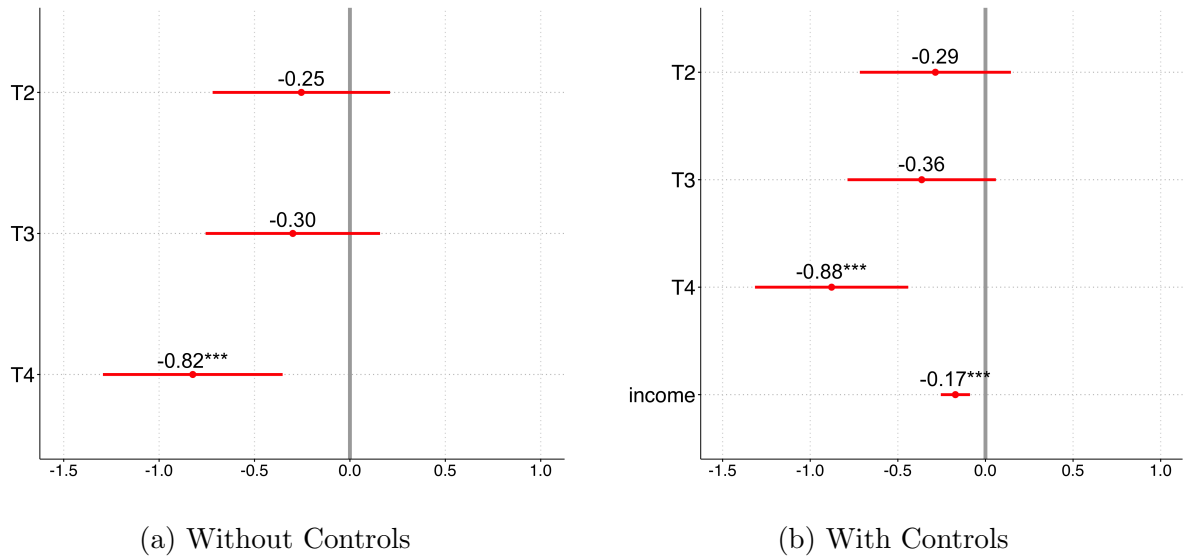


Figure 5.7: Estimated (S)ATEs via Regression

Tables C.2 and C.3 in Appendix C show the detailed regression outputs from regressing the outcome variable on the treatments, without and with covariates, with the original data and with multiple imputations, without and with sampling weights applied. The results in Table C.3 display a slightly smaller treatment effect of T4 when sampling weights are applied. This suggests that the estimated *sample* average treatment effect is not directly interpretable as an unbiased estimate of the *population*

average treatment effect. Nonetheless, the coefficients of T4 with or without the sampling weights are quite similar in terms of substantive and statistical significance.

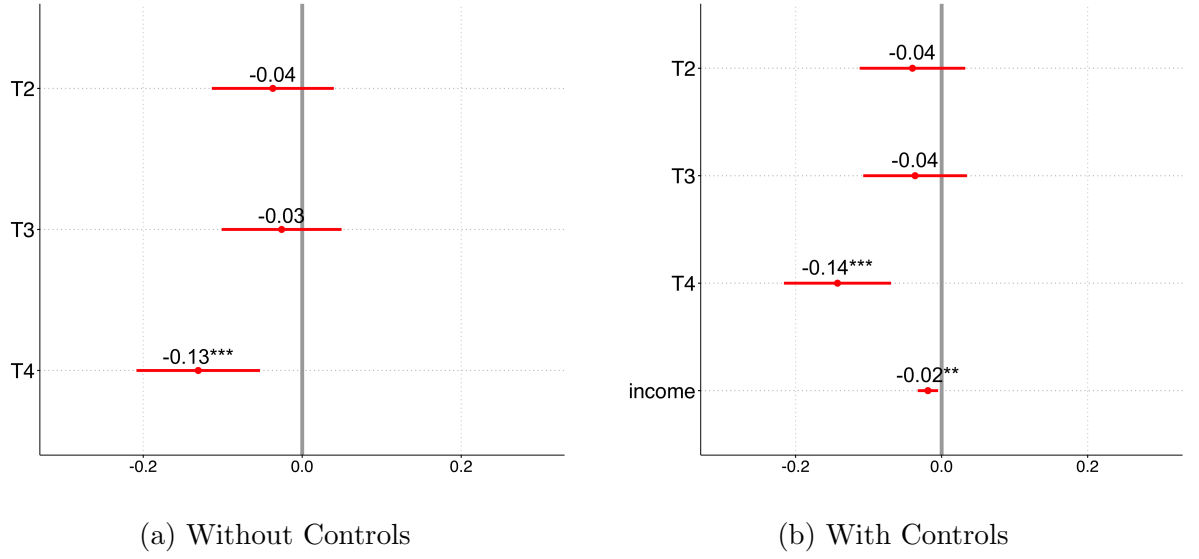


Figure 5.8: Estimated (S)ATEs via Regression with Binary Dependent Variable

As explained above, I also estimate the treatment effects on a binary version of the dependent variables, where responses of 6 or higher are coded as 1 and 5 or lower and missings are all coded as 0. The results of this are shown in Figure 5.8. Again, only the difference between treatment group 4 and control group is statistically significant. About 13% less respondents indicated support for income redistributive measures than in the control group. Once more, this is robust to the inclusion of controls and is about seven times the size of the coefficient of income.

All of the above described statistical tests point towards a negative effect of treatment T4 which does not seem to be due to chance. However, linear regression may not be the most appropriate estimator of the ATE, especially when relaxing the unconditional independence assumption and including other covariates. Angrist and Pischke (2009, 73-77) show that regression estimates a *conditional variance-weighted* ATE by putting more weight on subclasses in X_i where the variance of treatment is higher. In contrast, subclassification or matching yield the ATE by weighting the CATEs (see equation 5.8) *only* by the marginal distribution of the subclasses in X_i in the population.¹⁰ This “difference in weighting schemes is of little importance if δ_x [the CATE for subclass x] does not vary across cell” (Angrist and Pischke, 2009, 76). However, in this case there

¹⁰Or by the distribution of X_i in the treatment group for the ATT and the distribution of X_i in the control group for the ATT.

are good grounds to expect heterogeneous effects by income group, not least because the specific treatment vignette depends on individual’s household income to begin with. Therefore, I also estimate the average treatment effect on the treated (ATT) via matching.

Matching Estimator

There are many possible decisions to make when choosing which kind of matching strategy to apply. In fact, there is often “no single optimal choice for any given analysis” (Ho et al., 2021, `vignette("matching-methods")`), and “researchers should merely run as many [matching procedures] as possible and choose by maximizing balance” (Ho et al., 2007, 232). In simpler terms, the chosen matching strategy should yield a control group that is as similar as possible to the treatment group with respect to the chosen covariates, without taking into consideration the outcome variable.

One drawback of matching is that it is not well equipped to deal with non-binary treatments.¹¹ Therefore, I binarise the treatment variable, with $T4 = 1$ and zero otherwise. I perform 16 different matching procedures with the same covariates used in the regressions above, circling through combinations of 1) nearest neighbour matching with propensity score, Euclidean or Mahalanobis distances or genetic matching;¹² 2) with or without replacement; and 3) one match per treated unit (1:1 ratio) or two matches per treated unit (2:1 ratio).

The resulting remaining sample sizes and covariate balances (summarised by the mean absolute standardised bias) from each permutation are shown in Table 5.4 for $T4$ as the treatment of theoretical interest here.¹³ The last column reports the ATT estimated with the respective matched data and the rows corresponding to the procedure with the lowest bias within each distance measure are highlighted in bold italics.

All methods achieve an average standardised mean difference below 0.1, which is not very surprising given that covariate balance was already pretty good due to randomisa-

¹¹Although there are some recent developments within statistical science. See, for instance, Nattino et al. (2021) for an overview of the (little) attention given to matching designs with multiple treatments. The authors also introduce and apply a conditional three-way matching algorithm.

¹²Nearest neighbour matching is performed using the `MatchIt` package (Ho et al., 2011) and genetic matching by using functions included in the `Matching` package (Sekhon, 2011; Diamond and Sekhon, 2013) as called by the `MatchIt` package.

¹³Moreover, I apply these sixteen procedures once without and once with sampling weights. The results with sampling weights are shown in Appendix C.4.

Table 5.4: Bias & ATT's of T4 from different matches

Ratio	Replacement	Distance	N° obs	Bias	ATT
1	Yes	propensity score	563	0.039	−0.67*
1	No	propensity score	636	0.027	−0.69**
2	Yes	propensity score	752	0.034	−0.68**
2	No	propensity score	954	0.020	−0.61**
1	Yes	euclidean	580	0.057	−0.6*
1	No	euclidean	636	0.056	−0.55*
2	Yes	euclidean	769	0.059	−0.74***
2	No	euclidean	954	0.051	−0.82***
1	Yes	mahalanobis	554	0.011	−0.72**
1	No	mahalanobis	636	0.022	−0.54*
2	Yes	mahalanobis	729	0.017	−0.65**
2	No	mahalanobis	954	0.027	−0.65***
1	Yes	genetic	558	0.000	−0.77**
1	No	genetic	636	0.001	−0.61**
2	Yes	genetic	729	0.002	−0.66**
2	No	genetic	954	0.004	−0.64**

Note:

+p<0.1; *p<0.5; **p<0.01; ***p<0.001

Significance tests based on cluster-robust standard errors, clustered by matched pairs (or trios) when matching is performed without replacement and by matched pairs/trios and observation id when performed with replacement, as some control observations are used more than once as a match.

tion. Nonetheless, genetic matching¹⁴ with a 1:1 matching ratio and replacement yields the best covariate balance. Figure 5.9 shows the improvement in balance achieved. The standardised mean differences for each covariate are all zero or very close to zero. This is especially noteworthy for those identified as a possible source of bias in Figure 5.5, retirees and social grades DE and AB, which here as well are marked with the highest pre-match imbalance.

The associated estimated average treatment of vignette T4 on the treated is −0.77, which is statistically significant at a 99% confidence level. This effect is slightly less than the −0.88 estimated via regression. There are a couple of reasons for this, on top of the different weighting scheme used to aggregate from CATEs to the ATE(T)s. Most notably, the difference is due to the fact that the 'control' group is now all respondents that are not in treatment group T4.¹⁵ Figure 5.6 showed that the average support for

¹⁴Which “uses a search algorithm to iteratively check and improve covariate balance, and it is a generalization of propensity score and Mahalanobis Distance (MD) matching” (Diamond and Sekhon, 2013, 3).

¹⁵Of the control observations in the matched data set, 31% come from the control, 31% from group T2 and 38% from group T3.

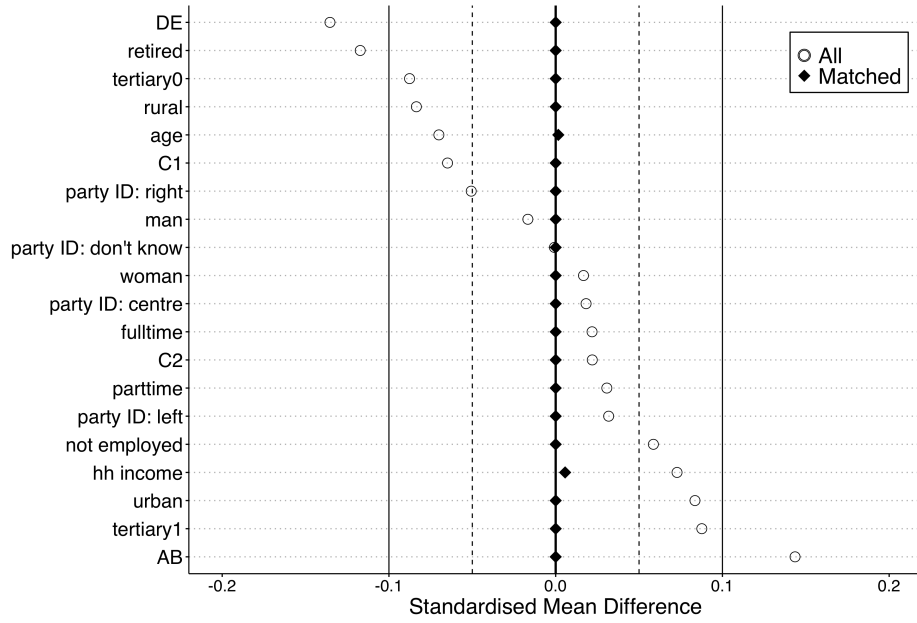


Figure 5.9: Balance before/after 1:1 genetic matching with replacement on T4

redistribution in groups T2 and T3, while being higher than T4, was lower than in the control group. Therefore, it is intuitive that the treatment effect estimated this way would be smaller. In fact, when 1:1 genetic matching with replacement is performed only on the subset of data only including treatment group 4 and control group, the estimated ATT is -0.81^{**} (based on 475 observations and a bias of 0.007 - see Table C.5). This goes to show that the negative effect of T4 appears not only distinguishable from no treatment, but also to some extent from each piece of information shown separately. This conclusion is robust to alternative matching procedures without and with sampling weights with ATT estimates ranging from about -0.44 to -0.87 (see tables 5.4 and C.4).

The same cannot be said about treatments T2 and T3. Table C.6 summarises the results of applying the same sixteen variations of matching on a subset of only the control observations and those in groups T2 and T3 respectively. Nearly all the estimated ATTs are negative, but smaller in magnitude than the equivalent estimates for T4 in Table C.5. None of the ones for T3 pass the 0.05 p-value threshold for statistical significance, and the estimate obtained with the match with lowest variance is -0.16 . Only one of the estimates for T2 obtained after 2:1 genetic matching with replacement (which also has the lowest bias) is statistically significant at a 95% confidence level and is -0.61 . The wider range in the absolute sizes and precision of these estimates, i.e.

the fact that the results are very sensitive to alternative specifications of the matching procedure, should guard against drawing any conclusions about the causal effects of T2 and T3 respectively. What can be said, however, is that the attitudinal patterns observed after exposure to the combination of the two vignettes are, in this experiment, systematically different from those in the control and in the other two treatment groups.

5.4.3 Heterogeneous Treatment Effects

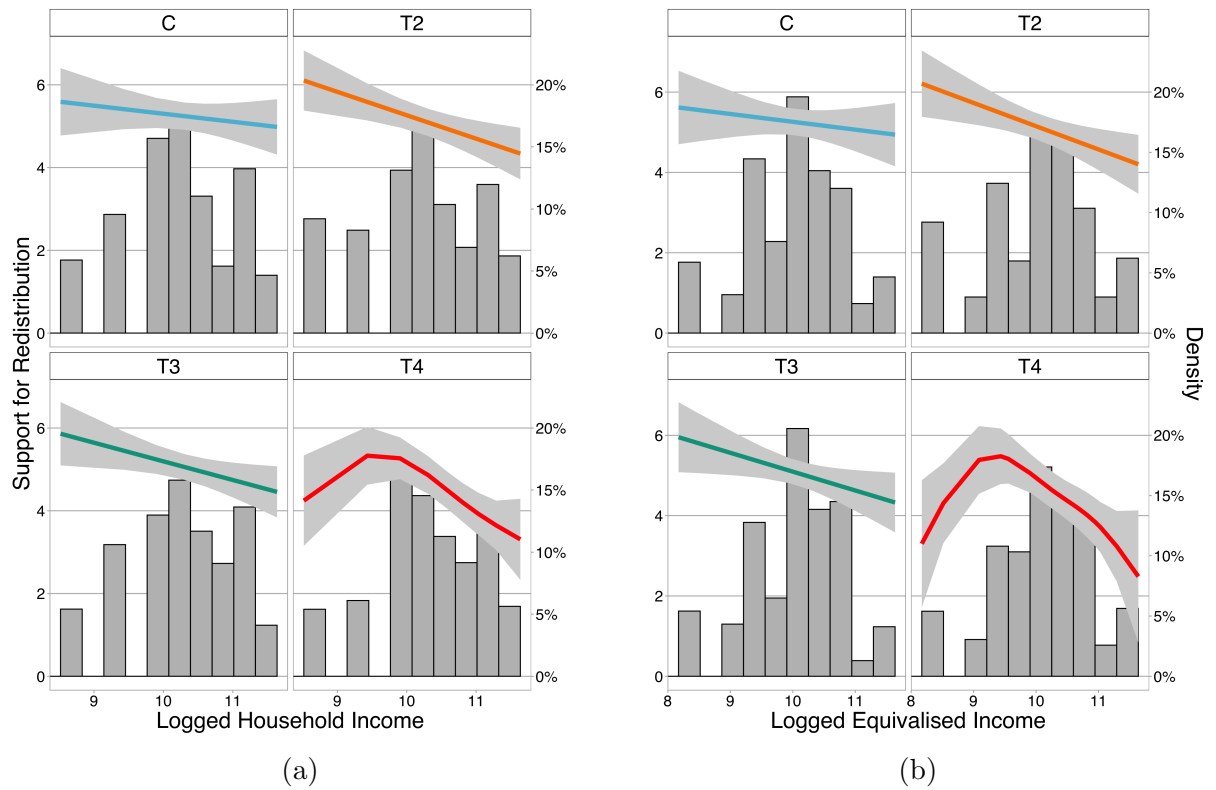
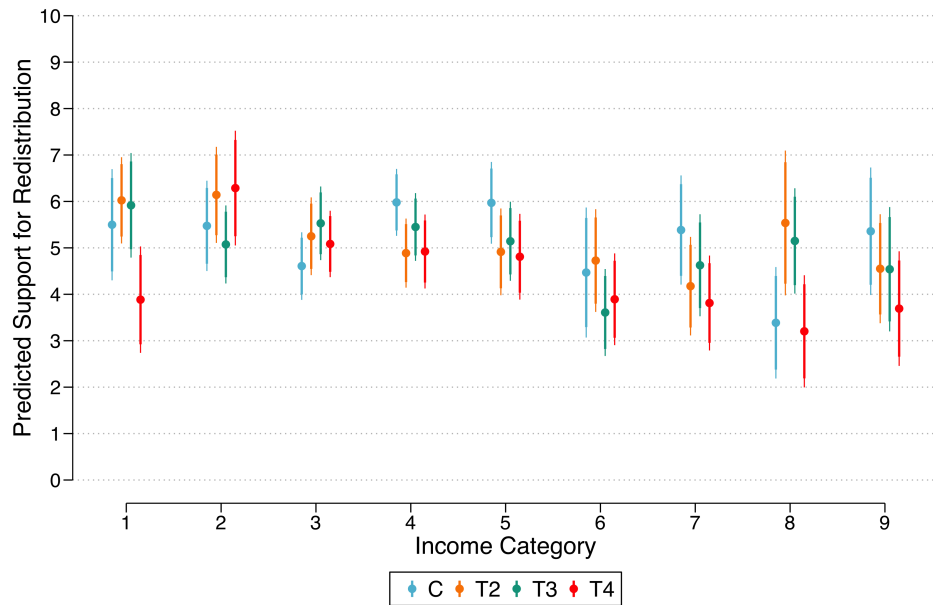


Figure 5.10: Support for redistribution by income and treatment group
Estimated with a generalised additive model (gam) with logged income as a smooth predictor with 5 knots interacted with treatment group assignment, yielding a separate smooth for each level of the factor.

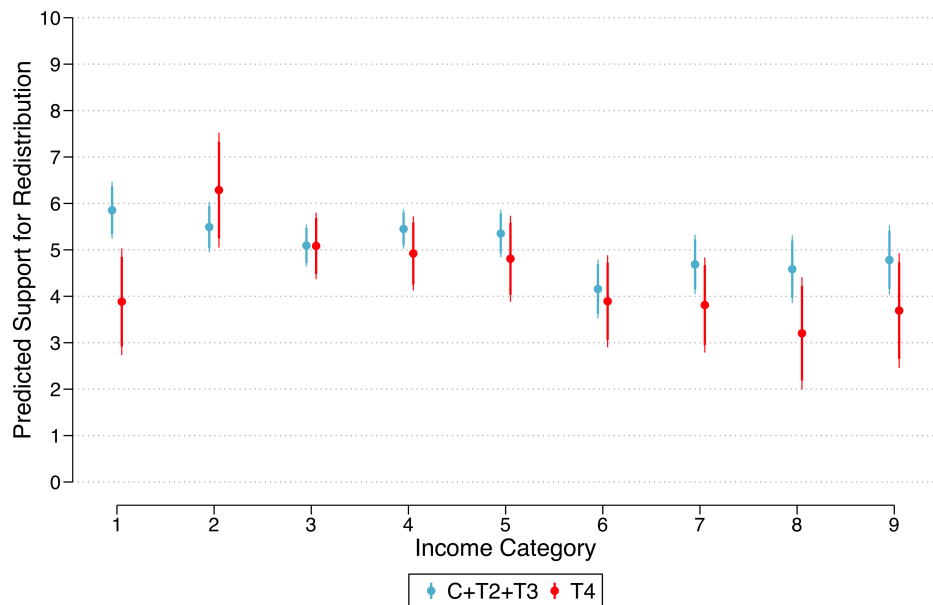
Figure 5.10 shows average support for redistribution by (a) logged household income and (b) logged equivalised income.¹⁶ The relationship is clearly linear in the control group and treatment groups T2 and T3, with a slightly shallower slope in the control group. In contrast, the shape of the curve within T4 is striking. Support among the poorest in T4 is about the same as that among the richest in T3 and T2. Yet, support

¹⁶Income is equivalised by dividing the midpoint recoded income by the square root of 2 if the respondent indicated that they were sharing a household with a life partner. This is done to better account for the financial resources truly available to the respondent's household *per head*.

is not uniformly lower across the income distribution and first rises to reach similar levels than in the other groups among lower middle incomes before dropping again by more than in the other groups.



(a) All Treatments



(b) Binary Treatment

Figure 5.11: Predictions from Regression with Interaction

The question then is whether any inferences can be made about this observable pattern, whether statistical or causal. One common approach is to simply interact treatment with the covariate of interest in a linear regression. Figure 5.11 displays the predicted support for redistribution for each income-treatment group and 95%

confidence intervals¹⁷ estimated via a linear regression with both the main effects for treatment status and income category, as well as their interaction.¹⁸ The top panel of Figure 5.11 shows the predicted outcomes for each of the four treatment categories. Quite strikingly, the estimate for T4 in the lowest income group is substantively lower than those in the control group, T2 and T3, of about 1.5 to 2 points less on a 0-10 scale. This difference is statistically significant to T2 and T3 (at at 95 and 90% confidence level respectively), although it is not relative to the control group. Nonetheless, no such divergence is apparent within the other income categories.¹⁹ The lower panel shows the results of an interaction of income category with a binary version of the treatment where T4 is compared to control, T2 and T3 together. The difference between T4 and the other groups is now statistically significant because the standard error of the estimate for the latter is now much smaller (i.e. precision has increased).

There is, however, an inherent challenge to so-called subgroup analysis in experimental research – that is to say the estimation of treatment effects for subgroups determined by observable covariates X , i.e. heterogeneous treatment effects. While successful randomisation can ensure balance on observable and unobservable confounders *in expectation* and therefore allows us to “safely average over subgroups” (Ratkovic, 2021, 271), the same does not follow within subgroups. Moreover, statistical power decreases quickly when partitioning an already small sample into further subsamples, especially in the absence of blocked randomisation (Mutz, 2011, 89-90).

These issues are also of relevance for this experiment, as is evidenced by the discussion of Figure 5.11 and also can be seen in Table 5.5. While the distribution is nearly fully balanced across treatment groups for the full sample, it is not the same within each income category. For instance, in category 2, only 17% of respondents were assigned to T4 and 33% to T3; in category 6, 17% were assigned to control and 32% to T3. Moreover, the absolute number of observations is quite uneven across income categories, with the most observations (283) in category 4 (£25,000-£34,999), and the least (80) in category 9 (Over £90,000). All this casts doubt on the meaningfulness of the estimates obtained via linear regression.

The challenge faced when choosing the appropriate estimator is thus twofold: first,

¹⁷90% confidence intervals are indicated by the end of the slightly thicker line.

¹⁸Sampling weights are applied.

¹⁹Moreover, the lack of precision is in large part due to the small sample size.

Table 5.5: Distribution of treatment groups within each income category

	Income Category									All
	1	2	3	4	5	6	7	8	9	
C	21%	26%	25%	26%	23%	17%	23%	25%	21%	23.6%
T2	36%	24%	22%	27%	23%	23%	27%	19%	30%	25.1%
T3	22%	33%	23%	26%	28%	32%	27%	30%	21%	26.7%
T4	21%	17%	30%	22%	25%	29%	23%	27%	27%	24.6%
All	112	150	258	283	192	133	128	97	89	1442

how to obtain *unbiased* estimates of the CATEs in each income category when the assumption of random assignment may be violated within a given subgroup; and, second, how to obtain *efficient* estimates of the CATEs in each income category when the sample size is very small within a given subgroup. In sum, “[l]earning subgroup effects and conducting inference on them is too much to ask of any single data set” (Ratkovic, 2021, 272).

An emerging approach initially proposed by Athey and Imbens (2016) and further developed by Wager and Athey (2018); Carvalho et al. (2019); Athey and Wager (2019) is to use the treatment effect itself as the outcome variable and find those variables which explain as much treatment effect heterogeneity as possible (Ratkovic, 2021, 277) via recursive partitioning. As such, this body of work proposes “causal” trees and forests as efficient and honest estimators of the CATEs. Decision trees work by consecutively splitting the data along dichotomous (or dichotomised) variables into leaves, finding the splits that maximise variance in the outcome variable. The growing of the decision tree stops when all observations on a leaf have the same outcome value or when a further split does not improve model fit any more. What makes the procedure ‘honest’ is that only a subsample of the data is used to grow the tree and identify the leaves and the remaining observations are used to predict the outcome (in this case the subgroup specific treatment effect). The advantage of random forests is that they average across many decision trees of which each use a different random subsample for training. Therefore, all observations are at one point used for training or predicting, but never both within one tree.

In this framework, following Wager and Athey (2018, 6), the conditional average

treatment effect τ_{bx} for tree b for any covariate $x \in L$ is estimated by:

$$\hat{\tau}_{bx} = \frac{1}{n_{1L}} \sum_{i=1}^{n_{1L}} Y_i - \frac{1}{n_{0L}} \sum_{i=1}^{n_{0L}} Y_i \quad (5.11)$$

where L is the leaf where the specific value of x can be found and n_{1L} and n_{0L} are the number of observations on leaf L of tree b in treatment and control group respectively. This is then averaged by the forest across the ensemble B of trees as follows:

$$\hat{\tau}_x = \frac{1}{B} \sum_{b=1}^B \hat{\tau}_{bx} \quad (5.12)$$

And the variance estimator is:

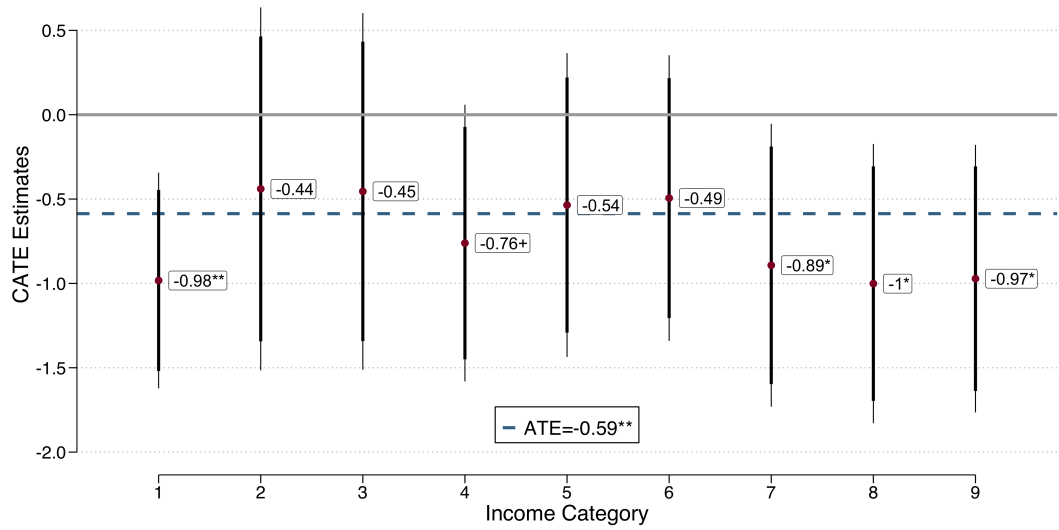
$$\hat{\sigma}_{\tau_x}^2 = \frac{n(n-1)}{(n-s)^2} \sum_{i=1}^n \left(\frac{\sum_{b=1}^B (\hat{\tau}_{bx} - \hat{\tau}_x)(N_{ib} - \bar{N}_i)}{B} \right)^2 \quad (5.13)$$

where n is the number of training examples (i.e. observations in the training data), s is the number of training examples randomly sampled from n used in the building of each causal tree b , N_{ib} indicates whether or not training example/observation i was used for the b -th tree (Wager and Athey, 2018, 7).

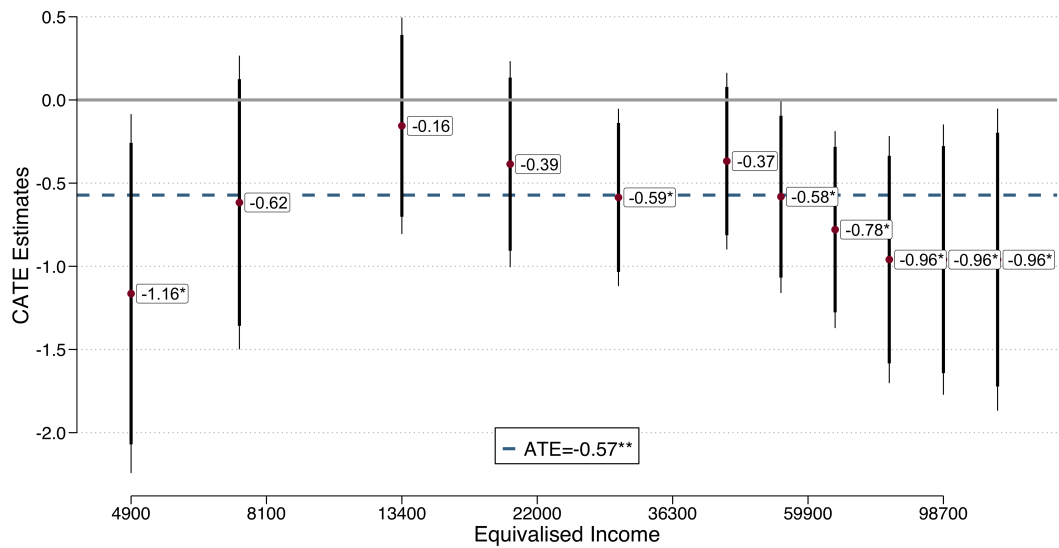
I estimate two sets of causal forests to estimate the (C)ATE of T4, including sampling weights. The first one uses, as splitting covariates, the nine income categories and a categorical age variable.²⁰ For the second one, I use logged income equivalised by whether the respondents lives with a partner. Both forests are composed of 10,000 causal trees, each tree being estimated with a random subsample half the size of the data. This subsample is then again split in two to use one half to place the splits and the other half to make the predictions.

Figure 5.12 displays the estimated average treatment effects of T4 *conditional* on (a) the respondent being in income category x and (b) the respondent having a logged equivalised income x . The boxes in the bottom middle of each plot report the ATE estimated with the causal forests. In either case, the estimate is statistically significant at the 99% confidence level and is about similar in magnitude as the estimates obtained via regression or matching with sampling weights. The labels next to each point state the point estimates and their respective statistical significance. The overlapping

²⁰Where respondents are split into the age groups 18-34, 35-59 or 60+ years old.



(a)



(b)

Figure 5.12: CATEs estimated via Causal Random Forests

confidence intervals – which may in large part be due to the small sample sizes – make it impossible to infer that the CATE estimates are statistically significantly different *from each other*. However, it is still possible compare the estimates for each income level based on whether they are statistically significantly different *from zero*.

Most notably, the CATE estimate for the lowest income level is negative and statistically significant from zero, whereas the subsequent two are still negative but not distinguishable from zero. Moreover, while all CATEs are estimated to be negative, the size of those estimates is largest (about 1 point on the 0-10 scale) for the top 3 income categories, *and the lowest one*. A similar tendency is apparent when using

logged equivalised income as the partitioning variable in the causal forest. Here, the largest CATE estimate (-1.16) is associated to the lowest income level.²¹

These results provide some support for the hypothesised non-linear effect across income, and in particular for the intuition that this should be relevant mostly for the poor. Then again, the effect for the rich is also negative. But it remains noteworthy that the effect of treatment for the poorest seems to be *as high* as the one for the richest, while the effect appears insignificant for intermediate levels of income. I will return to this in the discussion.

5.4.4 Preferred Tax Rates

As explained above, I used two other post-treatment questions to measure preferences related to redistribution. Specifically, I sought to capture the other side of the coin of redistribution: taxation. The first and main post treatment question that I used in the analyses above already made reference to taxation by explicitly linking the raising of taxes on everyone to the more equal redistribution of income by the government. The idea behind the two other questions was to more directly capture the ‘paying’ dimension of redistribution.

In hindsight however, especially the flat-tax item may have been unsuitable to capture whether respondents’ willingness to tax incomes was sensitive to treatment. Arguably, the main reason for this is that there is no flat tax on income in the UK, and that the treatments may have been overpowered by the lack of familiarity of respondents with a flat tax. This intuition is in line with the very high non-response (30% in the whole sample) to this post-treatment question, as can be seen in panel (a) of Figure 5.13. Clearly, a number of respondents did not know what to do with this question. Among those who did respond, the average preferred flat tax rate was about 24%.

The third post-treatment question asked respondents to set a separate tax rate for the bottom 60% and top 40% of the income distribution. The non-response rate (19%) is lower than for the flat-tax item, but still significantly higher than for the main post-treatment question.²² Panel (b) of Figure 5.13 shows the difference between

²¹Figure C.4 shows the results of a causal forest with, as outcome, the binary version of the dependent variable. It shows a similar pattern, whereby only the (negative) effects for the lowest and the top 4 income categories are statistically significantly different from zero.

²²Which was at 8%.

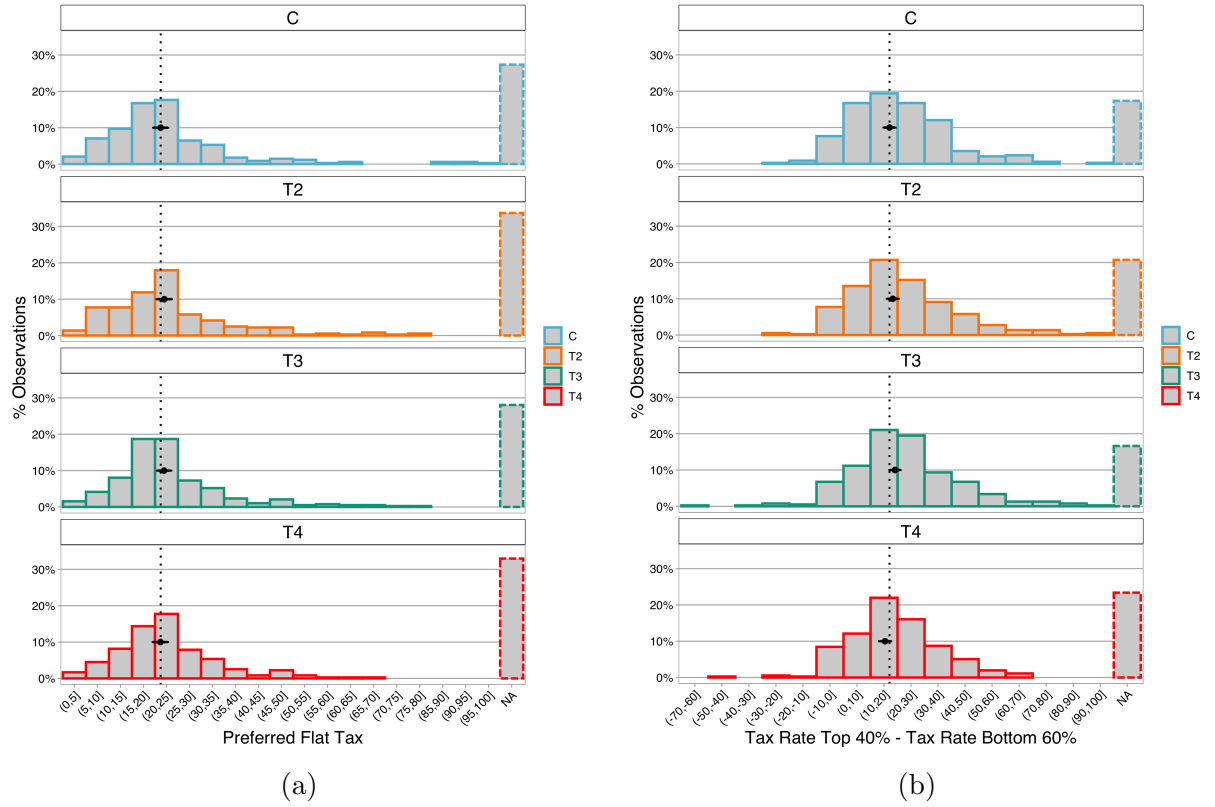
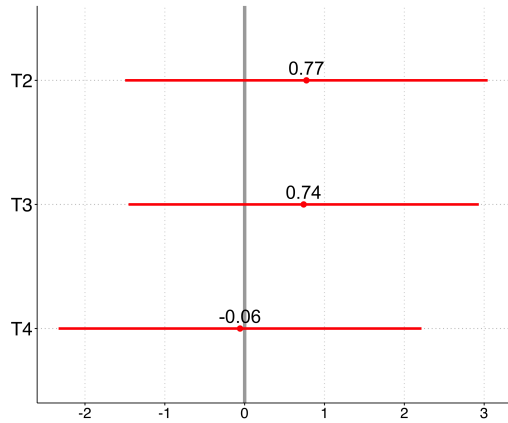


Figure 5.13: Preferred tax rates by treatment group

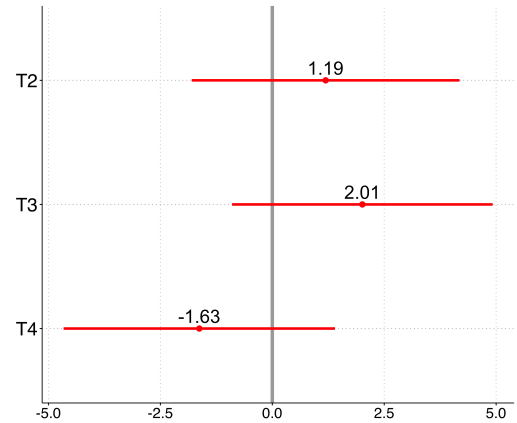
the two tax rates and thereby partly captures preferences about the progressivity of taxation. On average, respondents supported a tax rate for the richest 40% that is 22.5% higher than for the bottom 60%.

As both panels in Figure 5.13 suggest, the distributions do not appear to be obviously systematically different across the control and treatment groups.²³ For preferences over a flat income tax, this is clearly corroborated by the statistically insignificant treatment effect estimates displayed in panels (a - categorical treatment indicator) and (c - binarised treatment indicator) in Figure 5.14. Taking as a dependent variables the difference between the ‘high’ and ‘low’ income tax rates (panels (b) and (c)), respondents exposed to treatment vignette T4 seem to have been in support of slightly less progressive taxation (by about 1.6 percentage points less), whereas treatment groups T2 and T3 indicated to be, on average, supportive of a slightly higher tax rate for the rich than the poor (1.2 and 2 percentage points more respectively).

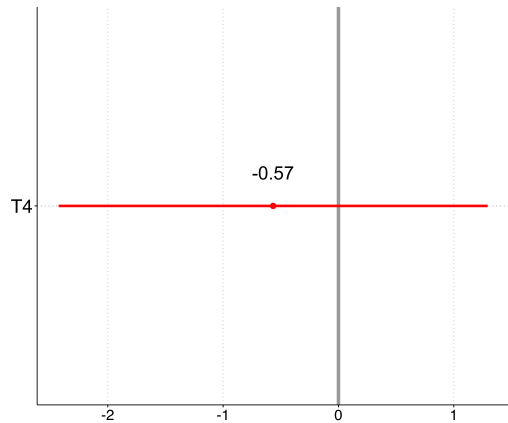
²³This is also the case when looking at the distributions by treatment group of the preferred tax rates for the bottom 60 and top 40% separately in Figure C.5. The preferred tax rate for the rich was on average around 43% with a standard deviation of 17.4% and 19.5% with a standard deviation of 11.5% for the poor.



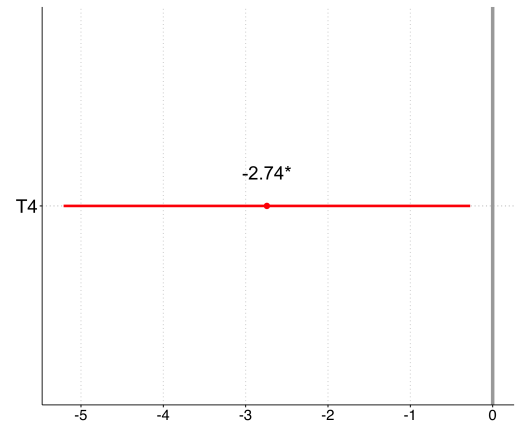
(a) Flat Tax
Control group average preferred flat tax is 24%.



(b) Top 40% - Bottom 60%
Control group average preferred difference in tax is 22%.



(c) Flat Tax – Binary Treatment
Control group, T2 & T3 average preferred flat tax is 24%.



(d) Top 40% - Bottom 60% – Binary Treatment
Control group, T2 & T3 average preferred difference in tax is 23%.

Figure 5.14: (S)ATE estimates of treatment on preferred tax rates

When using the binarised version of the treatment variable²⁴, the average difference in tax rates is 2.7 percentage points lower in T4 than in than control, T2 and T3 groups and statistically significant. However, this difference is only statistically significant at the 90% confidence level when including the same covariates as above. These results may hint towards the possibility of a negative effect of T4 on respondents' preferred level of progressive taxation. However, the lack of robustness of this result to alternative specifications and the high non-response rates to both questions caution against drawing anything more than purely suggestive conclusions from these analyses.

²⁴Where T4 is compared not just to the control group, but to all other groups.

5.5 Discussion

The purpose of this experiment was to test the effect on support for redistribution of increased salience of immigration, information about one’s position relative to those poorer in the income distribution and, most importantly, the combination of the two. In a way, these are quite ‘soft touch’ treatments, in the sense that no explicit causal link is made between immigration and income (re)distribution in the combination of the vignettes, except for the linking sentence “at the same time”. Another way of describing the taken approach is to call them ‘indirect’ treatments which “surreptitiously prime” or bring to mind a particular consideration without any misrepresentation” (Mutz, 2011, 50).

This was intended so as to not conflate the treatment from the mechanisms that are hypothesised to drive reactions to the treatment. It is argued that the individuals themselves implicitly would those causal links by reacting to the presence (or salience) of social heterogeneity with perceptions of economic status threat, which then are expected to lead to depressed support for income redistribution. Therefore, the experimental vignettes were designed such as to be indirectly suggestive but not so suggestive as to create Experimenter Demand Effects²⁵ (Mummolo and Peterson, 2019).

Another feature of this experiment was to contrast the effect of each priming information separately with their combination in one vignette. The drawback of such a design is the reduced sample size which makes a null-effect due to lack of statistical power more likely and also limits the interpretability of heterogeneous treatment effect estimates. It allowed me, however, to test the idea that it is the interaction of (perceptions of) the increase of immigration combined with awareness of one’s relative position in the income distribution that drives reduced support for redistribution and not either one of them alone.

The results described in section 5.4.2 are in line with these empirical expectations. Across different specifications and estimators, the effect of the combined vignette (T4) is negative and both statistically and substantively significant. Moreover, the estimated effects for T4 are persistently larger than the sum of the separate estimates for T2 and T3, which provides some evidence for an *interactive* effect, rather than simply additive.

²⁵Defined as “bias that occurs when participants infer the purpose of an experiment and respond so as to help confirm a researcher’s hypothesis” (Mummolo and Peterson, 2019)

For instance, in Figure 5.7 (a), $\hat{\tau}_{T4} = -0.82$, which is, in absolute terms, a 1.5 times larger effect than $\hat{\tau}_{T2} + \hat{\tau}_{T3} = -0.55$.

Substantively speaking, there seems to be something about the combination of increased awareness of one's position in the income distribution and increased salience of immigration which makes people less willing to support the government raising taxes and redistributing it. The question then is what is that something? This thesis' argument hypothesises a mechanism of positional competition within the income distribution, especially when the competition includes an out-group, leading to social status anxiety. However, this experiment does not really allow me to truly "unpack the black box of causality" (Imai et al., 2011, 785) and understand *how* the causal mechanism unfolds. The experiment did not include any manipulation checks which would allow me to investigate whether or not "experimental treatments have induced the intended differences by experimental condition in the independent variable" hypothesised to be driving the mechanism (Mutz, 2021, 219).

Specifically, I cannot directly test whether the treatment effects are driven by status competition, perceptions of (un)deservingness of recipients or (lack of) altruistic feelings. To a certain extent, treatment vignettes T2 and T3 that consist of half of T4 respectively are an indirect test of the mechanisms. If respondents - and especially the rich - were motivated mainly by altruism, information about their relative position in the income distribution alone (T2) should affect their redistributive preferences. Similarly, if the mechanism depends on beliefs about the undeservingness of immigrants, priming respondents only on the increased presence of immigrants (T3) - who have persistently been perceived as less deserving than other groups in society (Van Oorschot, 2006) - should also have an effect on support for redistribution. And yet, the results do not show substantively and statistically significant effects for the two vignettes. And yet, as already mentioned, these represent imprecise explorations of the precise causal mechanism. For sure, hindsight is 20/20.

One possible avenue could have been to measure subjective social status after treatment and after the outcome variables. For instance, I could have borrowed the survey item included in several rounds of the International Social Survey Programme (ISSP) which asks respondents to indicate their perceived position in society on a

ten-point social ladder.²⁶ I would expect respondents in treatment condition T4 to place themselves lower down than comparable respondents in the other groups. This could have been compared to possible alternative causal mechanisms by also including measures of beliefs about the deservingness of the poor²⁷ and of altruistic behaviour, for instance by incorporating a dictator game (c.f. Bekkers, 2007).

The investigation into potential heterogeneous treatment effects across income categories detailed in section 5.4.3, suggests that the poorest were more (negatively) reactive to the treatment than intermediate income categories and as (un)supportive of income redistribution as the richest three categories in treatment group T4. It should, furthermore, be kept in mind that the treatment of informing respondents about their relative position in the income distribution is, by design, not the same for rich and poor. Quite obviously so, because the poor will always be ranked lower than the rich on this dimension. As such, the nature of the treatment *could not* be independent of income. However, the small sample size and lack of subgroup level representativeness that arise from the partitioning of the data pose serious threats to both causal and statistical inference based on these results. One possible *ex ante* solution to estimating unbiased heterogeneous treatment effects would have been to use blocked randomisation, which would ensure that covariate balance is achieved within each income category.²⁸ What can nonetheless be said is that the poorest income category in the sample in treatment group T4 stands out by its low support for redistribution, both compared to the same category under other treatment conditions and to other income categories under the same treatment condition. This is suggestive of a treatment effect that is not uniform and not linear across the income distribution. Moreover, the notably strong negative effect in the bottom category is suggestive of a last place aversion mechanism (Kuziemko et al., 2014).

²⁶Precise wording is “*In our society, there are groups which tend to be towards the top and groups which tend to be towards the bottom. Below is a scale that runs from the top to the bottom. Where would you put yourself on this scale?*” See the documentation for the 2009 Social Inequality IV wave (ISSP Research Group, 2017). This survey question is used by Gidron and Hall (2017) and Engler and Weisstanner (2021) for instance, to study the relationship between (perceptions of) social status and voting for the populist right.

²⁷For instance, Van Oorschot (2006) uses the 1999/2000 wave of the European Values Study (EVS) that asks to what extent respondents feel concerned about the living conditions of various vulnerable groups. Alternatively, Cavaillé (2015) uses a series of survey items in the 2008 wave of the ESS that measure beliefs about the deservingness of recipients. In particular, the item “*Many people manage to obtain benefits and services to which they are not entitled*” could have served as a template.

²⁸See Cavaillé (2020) for an excellent primer on the subject.

5.6 Conclusion

In this chapter, I presented the motivation behind, design and results of a survey experiment. The aim of this experiment was to estimate the causal effect of the combination of increased salience of the ‘immigration issue’ with increased awareness of individuals’ relative position in the income distribution (looking down) on support for redistribution. The empirical expectation was that this informational treatment would make respondents less willing to support redistributive measures by the government. The theorised causal mechanism underpinning this hypothesis is that, under some circumstances, people will prioritise maximising the income distance between themselves and those poorer over the absolute material gains they could make from more redistribution. I argue that income differences serve as a signal for social status and are thereby endogenously legitimised by social hierarchy. This creates expectations that other dimensions of social status, and in particular ethnic and cultural differences, ought to ‘map’ onto the distribution of incomes. Therefore, in a context of heightened awareness of one’s position relative to those poorer and of increased salience of immigration, the compressing effect of redistribution on the income distribution will incite less enthusiasm for it.

Accordingly, a vignette experiment was conducted in May 2018 on a sample of 1,442 within the YouGov Omnibus survey. Respondents were asked a battery of questions about their socio-economic background and broad political orientation before treatment. The sample was then randomly split into four groups. The control group was not shown any vignette. The second group (T2) was only shown a vignette that told respondents the average income before and after transfers of those poorer than them and what proportion of the population these individuals represent based on the income bracket they placed themselves into. The third group (T3) was only shown a vignette that highlighted the increase of immigration over the last decades, notably and deliberately without any mention of the ethnic origin of immigrants. The fourth group (T4), was shown both vignettes together. Post-treatment, all respondents were asked to what extent they supported measures taken by the government to redistribute incomes in order to reduce differences between the rich and poor. In addition, all respondents were also asked what kind of tax rate would they set a) if everyone was taxed the same and

b) if there was a different tax rate for the bottom 60% and top 40% of incomes.

The results suggest that, indeed, the *combination* of those two pieces of information ‘curbed’ people’s preferred level of redistribution (as measured by the first post-treatment item) by a statistically and substantively significant amount. Evidently, linking together statements such as “This is how people poorer than you are faring before and after redistribution” and “Immigration has been increasing in the last couple of years” made respondents less enthusiastic about government taxing and then redistributing incomes. The next question is “why?”. As mentioned in the discussion above, this experiment does not allow me to retrace the causal mechanism in detail.²⁹ However, it does allow me to rule out that the effect is driven by either one of the treatment elements on its own. Across different specifications, groups T2 and T3 are not statistically significantly different from the control group and the sum of their estimates is smaller than the ATE estimate for T4. Moreover, that effect seems to be in part driven by the bottom income category. Descriptively, the poorest respondents in T4 stand out by their particularly low average level of support (3.9 vs. 5.9) of redistributive measures, as could be seen in Figure 5.11. Despite the difficulties posed by the small sample size to the estimation of unbiased conditional (heterogeneous) treatment effects, the observed pattern is quite striking.

Throughout the discussion above I have regularly pointed to the weaknesses of this experiment’s design. These, and, more broadly, what this experiment simply does not or cannot allow me to draw conclusions on are worth keeping in mind. First, while statistical power is rarely not an issue in any experiments, the four-way split of the sample does make the problem more acute. Still, the fact that a large and significant ATE is estimated by calculating differences between treatment groups is encouraging. However, this makes the estimation of conditional treatment effects by income more difficult, as discussed previously. Second, the categorical measure of household income poses limits to the accurate placement of respondents within the income distribution, which then fed into the treatment vignettes.³⁰ Calculating the bracket midpoints and from there deriving the average income and population share of those poorer may have

²⁹A possibly better designed experiment may have included relevant manipulation checks to be able to do so, although the increase of survey items may lead to an increase in attrition or survey satisficing.

³⁰The reason why many surveys use this type of item as opposed to open answers is to minimise the high item non-response usually associated with income. This is discussed in more detail in section 4.2.2.

been but a suboptimal approximation of it. Third, this experiment tested the effect of increasing *awareness* of one's position in the income distribution. It could not compare respondents who, at similar absolute income levels, were part of differently shaped gross income distributions. Therefore, it was not equipped to investigate the effect of the structure of inequality directly, and even less so the effect of *changes* in inequality.

More broadly, this points to the difficulties of making causal inferences about the effect of rising inequality on public opinion. There is a lot of academic literature, especially in economics and psychology, which seeks to assess the effect of inequalities in lab-experimental settings (e.g. Gee et al., 2017), with differences in incomes or endowments in experimental currency units and allocated within the experiment. This body of work is important to understand the behavioural and psychological reactions of individuals to precisely isolated differences in how and why income and wealth are distributed. However, it is very difficult to generalise these insights. In practice, inequality tends to evolve slowly, is often endogenous to many other social, economic and political trends and its economic and social consequences at the individual level are rarely observable in real time. In other words, it is hard to operationalise complex and incremental shifts in income distributions as interpretable 'treatments.' A similar point can be made about the studying the effect of immigration on public attitudes. In experimental settings, the causal effects of (simplified) in-group/out-group dynamics are being extensively studied and well documented. In contrast, when trying to assess the consequences of immigration for a whole national electorate for instance, it is much harder to pinpoint the how and the why. This is not to say that either causal or descriptive inferential work is not useful, but that it is crucial for researchers to be aware about what a chosen methodological approach allows one to do and not do. Our understanding of the mechanisms of social life is most likely to improve through the accumulation of research using a multitude of methods and perspectives.

Taken together, and notwithstanding the caveats outlined above, the results of this experiment do highlight something interesting about the reactions of the respondents. When told where they stood in the income distribution relative to those poorer, they were, on average, less willing to support income redistribution, but only when combined with information about the increased inflow of immigrants over the last decades. Evidently, they linked the two pieces of information, inferring that immigrants make up at least

some part of those ranked below them. The reasons *why* this resulted in lower support for redistribution are not directly testable within this experiment. In particular one aspect that further research should pay more attention to when studying the effects of inequality is trying to disentangle the role played by ordinal scaled ranks versus interval scaled differences between incomes. As it was, the experiment informed respondents both about their percentile rank *and* the mean income of those below. In contrast, the argument underpinning the last place aversion mechanism for instance are based on ranking (Kuziemko et al., 2014). Similarly, Kim (2019) presents an argument for why the poor may sometimes oppose redistribution based solely on people's fear of rank loss, not absolute differences in income. It is plausible that both one's rank and how close one's competitors are matter. More research is needed to understand better how they matter; separately, interactively, and in the context of social heterogeneity.

CONCLUSION | 6

In this thesis, I set out to answer the question of why the poor would be willing to pay the price of less redistribution in a context of increasing ethno-cultural heterogeneity, even if they benefit from redistribution. As such, the work in this thesis contributes to the research on the ‘immigrationization’ of the welfare state (Burgoon and Rooduijn, 2021). The argument I propose is that there is an extent to which people perceive differences in incomes between themselves and those poorer as justified, because they simultaneously reflect and confirm their own relative social status. Redistribution, as it compresses the income distribution, challenges this social ranking, heightens the acuteness of positional competition and consequently leads to feelings of resentment towards the people that make up the competition: those poorer than oneself. Resentment then leads to willingness to sacrifice parts of one owns’ material pay-offs to reduce those of the competition even more. This means that even people who are net beneficiaries of redistribution may become less supportive of it than their material calculation would predict. I also argue that people would be particularly willing to *pay for resentment* in a context of increasing ethno-cultural heterogeneity due to immigration. This argument has important implications for the role of inequality as well: whereas

I tested the implications of this theoretical mechanism in first instance observationally on time-series cross-sectional survey data from 25 European countries between 2000 and 2019 from the ESS and the ISSP. The results suggest that support for redistribution among the poor was lower in country-years with larger recent increases in the share of foreign-born population. Moreover, this pattern was more pronounced when the share of pre-tax income of the bottom 50% was smaller. Broadly speaking, these results are

in line with what the theoretical mechanism – and especially hypotheses 2, 3 and 4 – implies. However, as discussed in the conclusion of the corresponding chapter, it is not possible to consider such an observational design as test of the causal effect of the mechanism. It is difficult to control for all observable and unobservable confounders – in other words: account for alternative mechanisms – with these kinds of data.

Therefore, I also investigated the mechanism causally by means of an online survey experiment conducted in 2018 in the UK. The experiment was designed to estimate the causal effect of informing respondents about their position in the income distribution relative to those poorer as well as priming them on a recent increase of immigration. To be able to test whether differences in support for redistribution are driven by the combination of these two pieces of information and not just the one, the sample was randomly split into four groups that were exposed to either none, one or both of the vignettes. The results show that exposure to the combined vignettes was indeed associated with lower expressed support for income redistribution. Assuming (conditional) independence of treatment assignment and potential outcomes, the negative effect can be interpreted causally as an average treatment effect. There is also some evidence for a non-linear treatment effect dependent on income as the lowest income category in the main treatment group exhibited noticeably lower support than in the other groups and than the middle income categories. However, as the independence assumption is less likely to hold and statistical power is arguably too small when calculating these subgroup effects. Therefore, these findings are more tentative than the estimated main treatment effects.

Taken together, the findings discussed in the two empirical chapters can be summarised with the following takeaways. First, it is clear that any empirical approach has its limitations and it is important to be aware of these when drawing substantive conclusions from the results. Second, the role of the poor can not be dismissed from discussions about the relationship between immigration and support for redistribution. Third, the findings of the experiment in particular highlight the role of downwards social comparisons and people’s relative rank in a society.

Finally, the findings point to new avenues for future research into how socio-economic comparisons matter for support for redistribution and how this may be conditioned by existing inequality and ethno-cultural diversity. For instance, renewed interest should be

paid to the structure of inequality, not only as it determines net winners and losers from redistribution, but because it also structures social comparisons. Relatedly, I believe there is value in delving deeper into understanding how relative rank versus relative distance matter for people's way of seeing their place in society. More speculatively, it may be worth considering the role of the rise of social media in people's day-to-day lives and the constant comparisons it summons in shaping redistributive preferences.

Going back to the role of income inequality, the argument put forward in this thesis moves beyond simply considering the impact of more or less inequality. Indeed, the implication of my argument is that more immigration will lead to less support for redistribution when inequality is low in the bottom part of the income distribution – which may or may not be associated with lower overall inequality. More concretely, people who live in places where the distance between them and those slightly poorer and slightly richer is low would be those most easily convinced to turn against income redistribution when immigration (or the salience thereof) increases. More conjecturally, this theoretical mechanism could also provide some explanation for the popularity among lower income people of populist and radical right parties – which are not always that committed to more redistribution, as the examples in the introduction sought to highlight.

In a broader sense, the argument and the findings of this thesis speak to an emerging strain of research into how “people intertwine economic considerations with social and cultural considerations in the interpretations of the world they make with one another” Cramer (2016, 7) and how this affects modern politics. Notable examples are the recent work by Gidron and Hall (2017, 2020), Kurer (2020), Engler and Weisstanner (2021) or Bornschier et al. (2021). In resonance with this body of work, my argument seeks to account for how people's ‘objective’ economic circumstances feed into the perception of their social rank and value in society, which in turn affects how they evaluate those economic circumstances relative to others, and which ultimately affects their political preferences. The following captures the essence of this idea:

There is an odd asymmetry in the traditional ‘expected utility’ story whereby the observer (such as the decision analyst) learns about the chooser’s preferences by observing his decisions, but the chooser does not use the nature of the lotteries that he faces to learn about the nature of the world, which may affect his valuation of consequences and thus his choices.

– Sen (1985, 118)

In the end, it is a strange task to write a conclusion for a doctoral thesis. One started with the ambition to settle a debate or definitively tackle a question, and one finishes with many more questions and avenues for more debates. I believe that there is a need for more research into understanding the causes and consequences of the often intertwined feelings of economic, social and racial resentment that seem to characterise the political life of many developed democracies today.

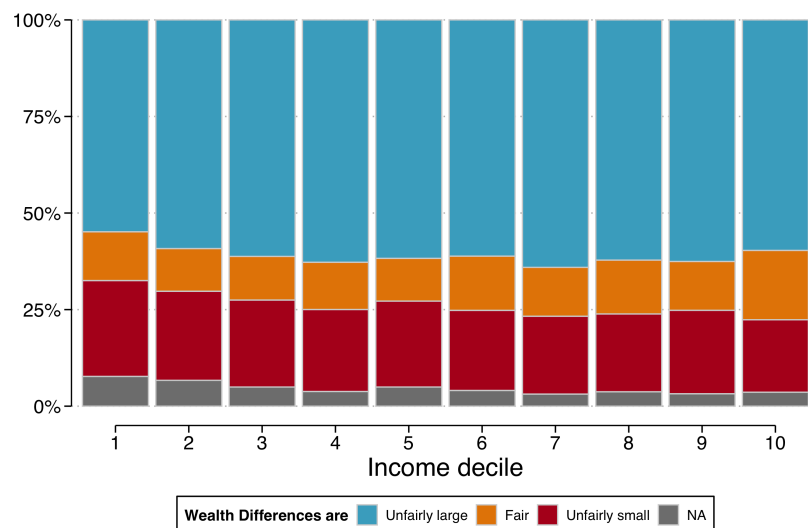


Figure 6.1: Perceived Fairness of Wealth Differences by Income Group in Western Europe

Note: The proportions are calculated so as to sum up to 1 within each income category. Post-stratification and population weights applied.

As mirror image to how I began this thesis, I would like to finish by pointing to a final empirical puzzle. I believe it illustrates how we still need to better understand why people deem some economic differences as justified, in turn limiting potential support for more redistribution. The 9th round of the ESS 2018 contained a module called “Justice and Fairness in Europe: Coping with Growing Inequalities and Heterogeneities.” Within this module, respondents were asked a series of questions about how they evaluate the ‘fairness’ of their own economic circumstances as well as inequalities in society. One of

these asked “In your opinion, are differences in wealth in [country] unfairly small, fair, or unfairly large?” that was measured on a scale from -4 (extremely unfairly small) to 4 (extremely unfairly large), with 0 indicating that wealth differences were ‘fair.’ Figure 6.1 shows the distribution of the responses by income decile averaged across the 15 Western European countries that I presented in my introduction.

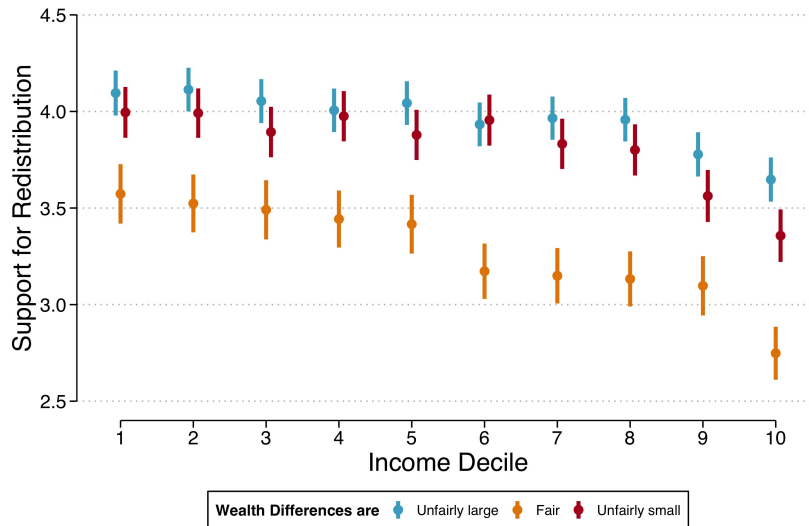


Figure 6.2: Perceived Fairness of Wealth Differences by Income Group and Support for Redistribution in Western Europe

Note: Point estimates based on a multilevel model with varying intercepts by country with 95% confidence intervals. Post-stratification and population weights applied.

It is important to note that, in each income category, a large majority found the wealth differences in their country unfairly large. However, the share of people that deemed them unfairly small varies between nearly 20% and 10% across incomes. Notably, it is the respondents in the lowest income decile that had the largest share of ‘unfairly small’ and there is a striking absence of any systematic variation across incomes. This is certainly surprising, especially in the face of the rise of high income and even higher wealth inequalities (Alvaredo et al., 2018). Figure 6.2 illustrates how these attitudes are related to support for redistribution within each household income group. More specifically, it shows that, within each income category, those who consider the existing wealth differences as ‘fair’ are also significantly less supportive of government redistribution. Those deeming wealth differences ‘unfairly small’ are overall only slightly less supportive than those that consider them ‘unfairly’ large of the statement that “the

government should take measures to reduce differences in income levels.”¹

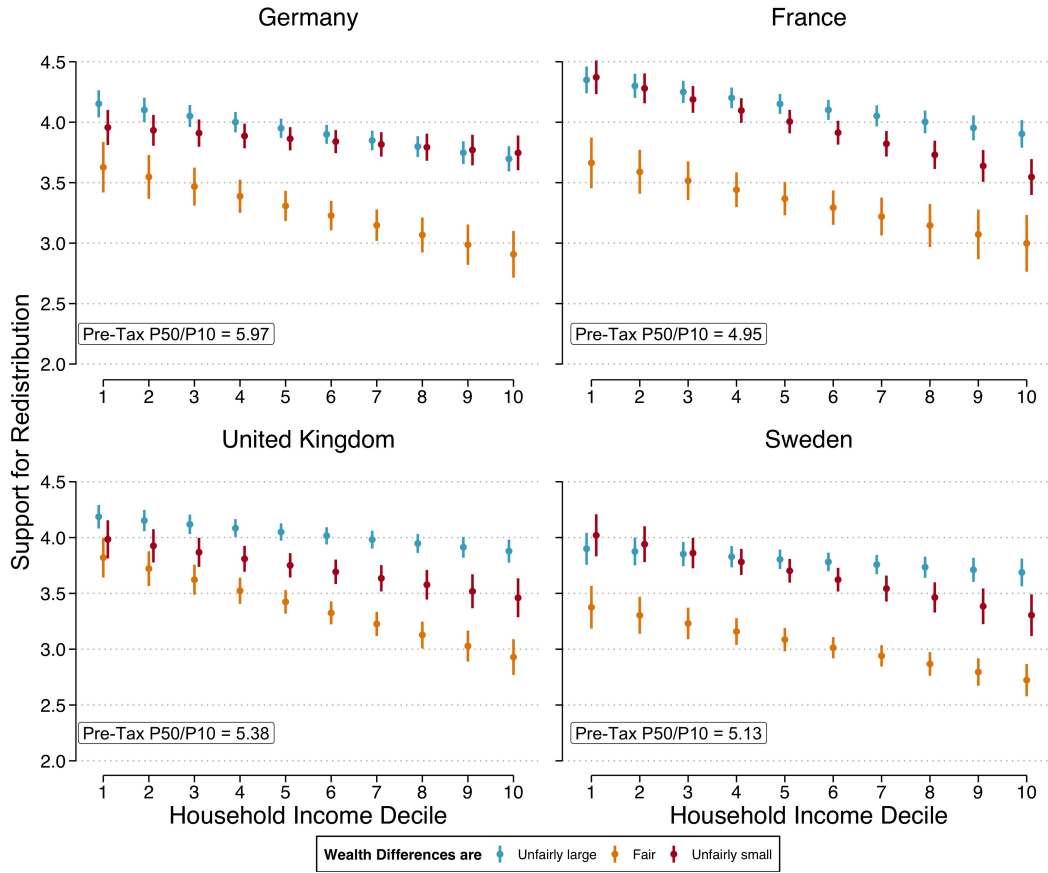


Figure 6.3: Perceived Fairness of Wealth Differences by Income Group and Support for Redistribution in Four Western Europe

Note: Point estimates based on a linear model for each country with 95% confidence intervals. Post-stratification weights applied.

Finally, Figure 6.3 disaggregates these relationships by country, in the four countries I highlighted in the introduction. The figures also list the pre-tax income threshold ratio between the 50th and 10th at the time of survey fielding (2018).² In France and Sweden – the countries with the lowest and second lowest ratio respectively – those who consider current wealth differences as fair are comparatively less supportive of redistribution, including – and especially – at low levels of income, compared to the other two countries. This is, in a way, in line with the argument of this thesis: when the income distribution is compressed at the bottom, people located at the bottom may come to consider income differences as *justified* (or: fair) and be less willing to support redistribution. Of course, this data is again purely descriptive and nearly anecdotal.

¹I do not have a good suggestion as to why those considering wealth differences *unfairly small* would still be more supportive of income redistribution than those deeming them *fair*. This may be evidence of some measurement miscalibration in either one of these survey questions.

²Like the ones used in chapter 4, these indicators are taken from the WID.

Nevertheless, it does, I believe, point towards the need for a better understanding of why and when existing economic inequalities are considered fair or not, and when people believe that government should do something about them.

Now, why do these people believe wealth differences – that are arguably less associated with individual effort and deservingness than earnings – to be *unfairly small* or even simply fair? Maybe part of the answer lies in the fact that people, whether poor or rich, care about preserving certain differences between economic circumstances to reflect a perceived social ranking. These final thoughts are speculative, of course, and are the sign that the point has been reached to truly conclude.

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APPENDICES

A Formal Model

A.1 Derivatives with respect to the tax rate

A.1.1 F.O.C. for equation 3.5

$$\frac{\partial V_i}{\partial t} = (1 - \beta)(-y_i + \bar{y} - t\bar{y})c_i^{-\epsilon} + \beta p_j(-y_i + \bar{y}_j)(p_j(c_i - \bar{c}_j))^{-\gamma} \quad (1)$$

$$(1 - \beta)(-y_i + \bar{y} - t\bar{y})c_i^{-\epsilon} = -\beta p_j(\bar{y}_j - y_i)(p_j(c_i - \bar{c}_j))^{-\gamma} \quad (2)$$

$$-y_i + \bar{y} - t\bar{y} = -\frac{\beta}{1 - \beta} p_j(\bar{y}_j - y_i) \frac{(p_j(c_i - \bar{c}_j))^{-\gamma}}{c_i^{-\gamma}} \quad (3)$$

$$-t\bar{y} = -\bar{y} + y_i - \frac{\beta}{1 - \beta} p_j(\bar{y}_j - y_i) \frac{(p_j(c_i - \bar{c}_j))^{-\gamma}}{c_i^{-\gamma}} \quad (4)$$

$$t^* = 1 - \frac{y_i}{\bar{y}} + \frac{\beta}{1 - \beta} p_j \frac{(\bar{y}_j - y_i)}{\bar{y}} \frac{c_i^{\epsilon}}{(p_j(c_i - \bar{c}_j))^{\gamma}} \quad (5)$$

A.1.2 S.O.C. for equation 3.5

Taking the second order condition shows that the marginal returns of $V_i(t)$ are decreasing.

$$\begin{aligned} \frac{\partial^2 V_i}{\partial t^2} &= (1 - \beta)[(-y_i + \bar{y} - t\bar{y})^2 u''(c_i) - \bar{y} u'(c_i)] + \beta[(-y_i + \bar{y}_j)p_j]^2 g''(p_j(c_i - \bar{c}_j)) \\ &= (1 - \beta)[(-y_i + \bar{y} - t\bar{y})^2 (-\epsilon c_i^{-\epsilon-1}) - \bar{y} c_i^{-\epsilon}] + \beta[(-y_i + \bar{y}_j)p_j]^2 (-\gamma)(p_j(c_i - \bar{c}_j))^{-\gamma-1} \end{aligned} \quad (6)$$

which is always negative, implying a concave utility.

A.1.3 F.O.C. for equation 3.7

$$\begin{aligned} \frac{\partial V_i}{\partial t} &= (1 - \beta)(-y_i + \bar{y} - t\bar{y})c_i^{-\epsilon} \\ &\quad + \beta [p_D(-y_i + \bar{y}_{jD})p_{jD}(p_{jD}(c_i - \bar{c}_{jD}))^{-\gamma} + p_I(-y_i + \bar{y}_{jI})p_{jI}(p_{jI}(c_i - \bar{c}_{jI}))^{-\gamma}] \\ t^* &= 1 - \frac{y_i}{\bar{y}} + \frac{\beta}{1 - \beta} \left[p_D \frac{\bar{y}_{jD} - y_i}{\bar{y}} p_{jD} \frac{c_i^{\epsilon}}{(p_{jD}(c_i - \bar{c}_{jD}))^{\gamma}} + p_I \frac{\bar{y}_{jI} - y_i}{\bar{y}} p_{jI} \frac{c_i^{\epsilon}}{(p_{jI}(c_i - \bar{c}_{jI}))^{\gamma}} \right] \end{aligned} \quad (7)$$

A.1.4 S.O.C. for equation 3.7

Taking the second order condition shows that the marginal returns of $V_i(t)$ are decreasing.

$$\begin{aligned} \frac{\partial^2 V_i}{\partial t^2} &= (1 - \beta)[(-y_i + \bar{y} - t\bar{y})^2 u''(c_i) - \bar{y} u'(c_i)] \\ &\quad + \beta[p_D((-y_i + \bar{y}_{jD})p_{jD})^2 g''(p_{jD}(c_i - \bar{c}_{jD})) + p_I((-y_i + \bar{y}_{jI})p_{jI})^2 g''(p_{jI}(c_i - \bar{c}_{jI}))] \\ &= (1 - \beta)[(-y_i + \bar{y} - t\bar{y})^2 (-\epsilon c_i^{-\epsilon-1}) - \bar{y} c_i^{-\epsilon}] + \beta[p_D((-y_i + \bar{y}_{jD})p_{jD})^2 (-\gamma)(p_{jD}(c_i - \bar{c}_{jD}))^{-\gamma-1} \\ &\quad + p_I((-y_i + \bar{y}_{jI})p_{jI})^2 (-\nu)(p_{jI}(c_i - \bar{c}_{jI}))^{-\nu-1}] \end{aligned} \quad (8)$$

which is always negative, implying a concave utility.

A.2 Partial derivatives and Cross Partial

A.2.1 Proof for $\partial V_i / \partial y_i$ and $\partial V_i / \partial d_i < 0$

According to the model, the preferred tax rate should decrease with respect to y_i and $d_i = p_j(y_i - \bar{y}_j)$. I prove this by totally differentiating equation 3.5. For simplicity, I refer to it as V'_i .

$$dV'_i = \frac{\partial V'_i}{\partial t} dt + \frac{\partial V'_i}{\partial y_i} dy_i + \frac{\partial V'_i}{\partial d_i} dd_i \quad (9)$$

$$\frac{dV'_i}{dy_i} = \frac{\partial V'_i}{\partial t} \frac{dt}{dy_i} + \frac{\partial V'_i}{\partial y_i} + \frac{\partial V'_i}{\partial d_i} \frac{dd_i}{dy_i} \quad (10)$$

Setting this to zero, we get:

$$\begin{aligned} \frac{dt}{dy_i} &= - \frac{\partial V'_i / \partial y_i + \partial V'_i / \partial d_i \frac{dd_i}{dy_i}}{\partial V'_i / \partial t} \\ &= - \frac{(1 - \beta)[-u'(c_i) + (-y_i + \bar{y} - t\bar{y})(1 - t)u''(c_i)] + \beta[-p_j g'(S_i) \\ &\quad + p_j(-y_i + \bar{y}_j)p_j(1 - t)g''(S_i)] + \beta[-g'(S_i) + p_j(-y_i + \bar{y}_j)(1 - t)g''(S_i)] \frac{dd_i}{dy_i}}{V''_i(t)} \\ &= - \frac{(1 - \beta)c_i^{-\epsilon} \left[-1 - \frac{\epsilon(1-t)(-y_i + \bar{y} - t\bar{y})}{c_i} \right] + \beta S_i^{-\gamma} [-p_j + p_j \gamma] + \beta S_i^{-\gamma} [-1 + \gamma] \frac{dd_i}{dy_i}}{V''_i(t)} \end{aligned} \quad (11)$$

Since the denominator is always negative (see equation 6), the direction of the effect will depend on the the nominator. For $y_i < \bar{y} - t\bar{y}$, the first term is always negative. In the contrary case, the first term reduces to:

$$(\epsilon - 1)y_i - \epsilon(1 - t)\bar{y} - \frac{T(t)}{(1 - t)} < 0 \quad (12)$$

which is true for all $\epsilon \in (0, 1)$. The second and third terms in the nominator reduce to:

$$S_i^{-\gamma} p_j (-1 + \gamma) < 0 \quad (13)$$

$$S_i^{-\gamma} (-1 + \gamma) \frac{dd_i}{dy_i} < 0 \quad (14)$$

which is true in both cases for all $\gamma \in (0, 1)$, since $\frac{dd_i}{dy_i}$ is always positive.

Now, taking the total derivative with respect to income distance (pre-tax relative satisfaction) $d_i = p_j(y_i - \bar{y}_j)$ gives:

$$\frac{dV'_i}{dd_i} = \frac{\partial V'_i}{\partial t} \frac{dt}{dd_i} + \frac{\partial V'_i}{\partial d_i} \quad (15)$$

$$\begin{aligned} \frac{dt}{dd_i} &= -\frac{\partial V'_i / \partial d_i}{\partial V'_i / \partial t} \\ &= -\frac{\beta[-S_i^{-\gamma} + (-y_i + \bar{y}_j)p_j(-\gamma)S_i^{-\gamma-1}]}{V''_i(t)} \\ &= -\frac{\beta[S_i^{-\gamma}(\gamma - 1)]}{V''_i(t)} \end{aligned} \quad (16)$$

Once more, since the denominator is always negative, the sign of $\partial V_i / \partial d_i$ depends on the nominator, which is negative for all $\gamma \in (0, 1)$.

A.2.2 Proof for $\frac{\partial^2 t}{\partial y_i \partial d_i} > 0$

Secondly, in order to show that the effect of S_i decreases with income, I need to show that the cross-partial $\frac{\partial^2 t}{\partial y_i \partial d_i} > 0$. This means I have to take the derivative of equation 16 with respect to y_i .

$$\frac{\partial}{\partial y_i} \left(\frac{\partial t}{\partial d_i} \right) = \frac{\frac{\partial^2 V'_i}{\partial y_i \partial d_i}(-V''_i(t)) - V''_i(d_i) \frac{\partial^2(-V'_i)}{\partial y_i \partial t}}{(-V''_i(t))^2} \quad (17)$$

Keeping in mind that $\frac{dV_i}{dy_i} = \frac{\partial V'_i}{\partial y_i} + \frac{\partial V'_i}{\partial t} \frac{\partial t}{\partial y_i} + \frac{\partial V'_i}{\partial d_i} \frac{dd_i}{dy_i}$, which can be substituted into $\frac{\partial^2 V'_i}{\partial y_i \partial d_i}$, this yields:

$$\frac{\partial}{\partial y_i} \left(\frac{\partial t}{\partial d_i} \right) = \frac{\left(\frac{\partial^2 V'_i}{\partial y_i \partial d_i} + \frac{\partial^2 V'_i}{\partial t \partial d_i} \frac{dt}{dy_i} + \frac{\partial^2 V'_i}{\partial d_i \partial d_i} \frac{dd_i}{dy_i} \right) (-V''_i(t)) - V''_i(d_i) \left(\frac{\partial^2(-V'_i)}{\partial y_i \partial t} + \frac{\partial^2 V'_i}{\partial t \partial t} \frac{dt}{dy_i} + \frac{\partial^2 V'_i}{\partial d_i \partial t} \frac{dd_i}{dy_i} \right)}{(-V''_i(t))^2} \quad (18)$$

Factoring out $S_i^{-\gamma}\beta$ out of both $V''_i(S_i)$ and $V''_i(t)$, I can write equation 17 as:

$$\frac{\partial^2 t}{\partial y_i \partial d_i} = \frac{\frac{\partial A}{\partial y_i}(BC + D) - A(\frac{\partial B}{\partial y_i}C + \frac{\partial C}{\partial y_i}B + \frac{\partial D}{\partial y_i})}{(BC + F)^2} \quad (19)$$

where:

$$A = \gamma - 1 < 0 \quad (20)$$

$$B = \frac{1 - \beta}{\beta} \left(\frac{c_i^{-\epsilon}}{S_i^{-\gamma}} \right) > 0 \quad (21)$$

$$C = \frac{\epsilon(-y_i + \bar{y} - t\bar{y})^2}{c_i} + \bar{y} > 0 \quad (22)$$

$$D = -\frac{\gamma(p_j(y_i - \bar{y}_j))}{1 - t} > 0 \quad (23)$$

It is easily observable that $\frac{\partial A}{\partial y_i} = 0$. Furthermore, A is always negative for all $\gamma \in (0, 1)$. Therefore, and as B , C and D (and the denominator) are always positive, the sign of the overall term will depend on the derivatives of B , C and D . Before discussing the latter, it is important to note that:

$$\text{if } -y_i + \bar{y} - t\bar{y} < 0 \implies t > 1 - \frac{y_i}{\bar{y}} \quad (24)$$

$$\text{if } -y_i + \bar{y} - t\bar{y} > 0 \implies t < 1 - \frac{y_i}{\bar{y}} \quad (25)$$

In the first case, the tax rate is higher, and in the second lower than the one that would maximise material self-interest. First we have:

$$\begin{aligned} \frac{\partial B}{\partial y_i} &= \frac{\partial B}{\partial y_i} + \frac{\partial B}{\partial t} \frac{dt}{dy_i} + \frac{\partial B}{\partial d_i} \frac{dd_i}{dy_i} \\ &= \frac{1-\beta}{\beta} \left[\frac{(1-t)(-\epsilon)c_i^{-\epsilon-1}S_i^{-\gamma} - c_i^{-\epsilon}(1-t)p_j(-\gamma)S_i^{-\gamma-1}}{S_i^{-2\gamma}} \right. \\ &\quad + \frac{(-y_i + \bar{y} - t\bar{y})(-\epsilon)c_i^{-\epsilon-1}S_i^{-\gamma} - (-y_i + \bar{y}_j)p_j(-\gamma)S_i^{-\gamma-1}}{S_i^{-2\gamma}} \frac{dt}{dy_i} - \\ &\quad \left. c_i^{-\epsilon}(1-t)(-\gamma)S_i^{-\gamma-1} \frac{dd_i}{dy_i} \right] \\ &= \frac{1-\beta}{\beta} \frac{S_i^\gamma}{c_i^\epsilon} \left[(1-t) \left(\frac{\gamma}{c_i - \bar{c}_j} - \frac{\epsilon}{c_i} \right) + \left(-\frac{\epsilon(-y_i + \bar{y} - t\bar{y})}{c_i} - \frac{\gamma}{1-t} \right) \frac{dt}{dy_i} \right. \\ &\quad \left. + \frac{\gamma}{p_j(y_i - \bar{y}_j)} \frac{dd_i}{dy_i} \right] \end{aligned} \quad (26)$$

The first term inside the square brackets is positive for all $\gamma \geq \epsilon \frac{c_i - \bar{c}_j}{c_i}$, which is the same result than the one found in equation 3.13. The last term is clearly positive as well. As $\frac{dt}{dy_i}$ is negative, the second term is positive overall if $y_i < \frac{\gamma}{\epsilon} y_i + \frac{\gamma}{\epsilon} \frac{T(t)}{1-t} + (1-t)\bar{y}$, which is always true as long as $\gamma > \epsilon \frac{y_i - (1-t)\bar{y}}{y_i + \frac{T(t)}{1-t}}$.³ Next we have:

$$\begin{aligned} \frac{\partial C}{\partial y_i} &= \frac{\partial C}{\partial y_i} + \frac{\partial C}{\partial t} \frac{dt}{dy_i} \\ &= -\frac{2\epsilon(-y_i + \bar{y} - t\bar{y})}{c_i} - \frac{(1-t)\epsilon(-y_i + \bar{y} - t\bar{y})^2}{c_i^2} \\ &\quad + \left(-\frac{2\epsilon\bar{y}(-y_i + \bar{y} - t\bar{y})}{c_i} - \frac{\epsilon(-y_i + \bar{y} - t\bar{y})^3}{c_i^2} \right) \frac{dt}{dy_i} \\ &= \frac{\epsilon(-y_i + \bar{y} - t\bar{y})}{c_i} \left[-2 - \frac{(1-t)(-y_i + \bar{y} - t\bar{y})}{c_i} + \left(-2\bar{y} - \frac{(-y_i + \bar{y} - t\bar{y})^2}{c_i} \right) \frac{dt}{dy_i} \right] \end{aligned} \quad (27)$$

The sign of this term depends on whether the tax rate is above or below the material-self interest model. Taking the case where $t < 1 - \frac{y_i}{\bar{y}}$, $-y_i + \bar{y} - t\bar{y}$ will be positive, which will make the two first terms negative and the two within the round brackets positive

³This term can only become 1 at maximum for $t = 1$ and will further decrease towards $1 - \frac{\bar{y}}{y_i}$ as $t \rightarrow 0$.

because $\frac{dt}{dy_i} < 0$. The overall term will remain positive as long as the latter two times $\frac{dt}{dy_i}$ are bigger than the former two. This is the case as long as the marginal change in tax rate dependent on income $\frac{dt}{dy_i}$ is $< -\frac{2c_i+(1-t)(-y_i+\bar{y}-t\bar{y})}{2c_i\bar{y}+(-y_i+\bar{y}-t\bar{y})^2}$. As $-y_i + \bar{y} - t\bar{y} \rightarrow 0$, this reduces to $\frac{dt}{dy_i} < -\frac{1}{\bar{y}}$, which will stop being true as income increases. Consequently, this term is positive overall as long as the preferred tax rate is lower than the one maximising material self interest when $t > 1 - \frac{y_i}{\bar{y}}$, only the first term will be positive, and as $\frac{dt}{dy_i}$ reaches the threshold of $-\frac{1}{\bar{y}}$, $\frac{\partial C}{\partial y_i} < 0$.

And lastly:

$$\begin{aligned}\frac{\partial D}{\partial y_i} &= \frac{\partial D}{\partial y_i} + \frac{\partial D}{\partial t} \frac{dt}{dy_i} + \frac{\partial D}{\partial d_i} \frac{dd_i}{dy_i} \\ &= \frac{\gamma p_j}{1-t} + \left[\frac{\gamma p_j (y_i - \bar{y}_j)}{(1-t)^2} \right] \frac{dt}{dy_i} + \left[\frac{\gamma}{1-t} \right] \frac{dd_i}{dy_i} \\ &= \frac{\gamma}{1-t} \left(p_j + \left[\frac{p_j (y_i - \bar{y}_j)}{1-t} \right] \frac{dt}{dy_i} + \left[1 \right] \frac{dd_i}{dy_i} \right)\end{aligned}\tag{28}$$

Clearly, the sign of the overall term depends on $\left[\frac{p_j (y_i - \bar{y}_j)}{1-t} \right] \frac{dt}{dy_i}$. As $t \rightarrow 0$ and $\frac{dt}{dy_i} \rightarrow 0$ with increasing income, the term will go from negative to positive when $\frac{dt}{dy_i} > -\frac{2(1-t)}{y_i - \bar{y}_j}$, making $\frac{\partial D}{\partial y_i}$ positive overall. All the above goes to show that the negative effect of S_i decreases with income, explaining the curvature in Figure 3.4.

A.3 Proof for $\partial V_i / \partial d_{iD} < 0$, $\partial V_i / \partial d_{iI} < 0$ and $\partial V_i / \partial d_{iD} > \partial V_i / \partial d_{iI}$

Recalling that $p_D = 1 - p_I$, $d_{iD} = p_{jD}(y_i - \bar{y}_{jD})$ and $d_{iI} = p_{jD}(y_i - \bar{y}_{jI})$, the total derivative of equation 3.7 is as follows:

$$dV'_i = \frac{\partial V'_i}{\partial t} dt + \frac{\partial V'_i}{\partial y_i} dy_i + \frac{\partial V'_i}{\partial d_{iD}} dd_{iD} + \frac{\partial V'_i}{\partial d_{iI}} dd_{iI}\tag{29}$$

which leads to:

$$\frac{dV'_i}{dd_{iD}} = \frac{\partial V'_i}{\partial t} \frac{dt}{dd_{iD}} + \frac{\partial V'_i}{\partial d_{iD}} \quad \text{or} \quad \frac{dV'_i}{dd_{iI}} = \frac{\partial V'_i}{\partial t} \frac{dt}{dd_{iI}} + \frac{\partial V'_i}{\partial d_{iI}} \quad \text{respectively}\tag{30}$$

$$\frac{dt}{dd_{iD}} = -\frac{\partial V'_i / \partial d_{iD}}{\partial V'_i / \partial t} = -\frac{\beta[S_{iD}^{-\gamma}(\gamma - 1)]}{V''_i(t)}\tag{31}$$

$$\frac{dt}{dd_{iI}} = -\frac{\partial V'_i / \partial d_{iI}}{\partial V'_i / \partial t} = -\frac{\beta[S_{iI}^{-\nu}(\nu - 1)]}{V''_i(t)}\tag{32}$$

Both equations are negative as long as $\gamma \in [0, +\infty)$ and $\nu \in [0, +\infty)$. This shows that the relative size of these two parameters is pivotal to the argument. Hence, the

important element to prove here is when the following is true:

$$\begin{aligned}
\frac{dt}{dd_{iD}} &> \frac{dt}{dd_{iI}} \\
-\frac{\partial V'_i / \partial d_{iD}}{\partial V'_i / \partial t} &> -\frac{\partial V'_i / \partial d_{iI}}{\partial V'_i / \partial t} \\
-\frac{\beta[S_{iD}^{-\gamma}(\gamma-1)]}{V''_i(t)} &> -\frac{\beta[S_{iI}^{-\nu}(\nu-1)]}{V''_i(t)} \Leftrightarrow \\
S_{iD}^{-\gamma}(\gamma-1) &> S_{iI}^{-\nu}(\nu-1) \Leftrightarrow \\
S_{iI}^{-\nu}(\nu-1) - S_{iD}^{-\gamma}(\gamma-1) &< 0
\end{aligned} \tag{33}$$

Assuming a full and equal overlap of immigrant and domestic income distribution, $S_{iD} = S_{iI}$ and therefore, it is possible to write $S_{iI}^{-\nu}$ and $S_{iD}^{-\gamma}$ as constants a with different exponentials. Therefore,

$$\frac{\nu-1}{a^\nu} - \frac{\gamma-1}{a^\gamma} < 0 \tag{34}$$

Clearly, when $\nu = \gamma$, the effect is the same across all groups, as equation 34 is then equal to zero. As long as $\nu > \gamma$, however, $\nu-1 < \gamma-1$ and $a^\nu > a^\gamma$, leading to equation 34 being satisfied.

A.4 Comparing to conditional altruism

In this section, I contrast the model adding relative position into the utility function with one that includes both overall inequality as well as relative position. As such, I acknowledge that the effect of economic inequality can go through both perspectives at once.

Before separating between in-group (native-born population) and out-group (here: immigrants), and following Dimick et al. (2017), I formalise altruism by extending the utility function by the term Ω which symbolises the average of all other utilities in the form of an additive welfare function. This implies that if the average utility is below the average income, this second term will lead individual i to support redistribution more than her own material circumstances would predict.⁴ $\alpha_i \in (0, 1)$ parametrises the degree of altruism an individual i experiences. Summarising the self-interested part as $U(c_i)$, we come to the following utility function:

$$\begin{aligned}
V_i &= (1 - \alpha)U(c_i) + \alpha\Omega \\
&= (1 - \alpha)U(c_i) + \alpha \frac{1}{n} \sum_{j=1}^n U(c_j) \\
&= (1 - \alpha)U(c_i) + \alpha U(c_e)
\end{aligned} \tag{35}$$

$U(c_e)$ has the form $U(c_e) = \frac{c_e^{(1-\eta)}}{1-\eta}$ and is the utility gained from the “equally distributed equivalent income”, a concept introduced by Atkinson (1970). It is defined as “the

⁴Dimick et al. (2017) use the Atkinson inequality index which is 1 minus the ratio of average *utility* and average consumption. Because of non-linear and concave individual utilities, average utility will be increasingly lower than average consumption, the more income is disproportionately distributed (inequality aversion). Therefore social welfare will be reduced.

income per head which if equally distributed would give the same level of social welfare as the present distribution” (Atkinson, 1970, 250), and the evaluation of social welfare depends on value judgements over the relative importance of efficiency versus equality. This is ultimately about how much very low incomes are weighed against high ones, and is embodied by the inequality-aversion parameter η . Dimick et al. (2017) rearrange the formula for the Atkinson index to get to the following: $V_i = (1 - \alpha_i)U(c_i) + \alpha_i U[\bar{c}(1 - A)]$. Therefore, a higher Atkinson index A (i.e. higher inequality) leads to higher support for redistribution to reduce that inequality.

So far this is nothing new. But what happens if diversity, say in the form of increased immigration, is brought into the mix? One of the other advantages of the Atkinson Index, next to the value-based inequality measurement, is that it is decomposable (albeit not additively). Following Das and Parikh (1981), c_e (the equally distributed equivalent income for total population) can also be expressed as the “the mean of order $\beta = 1 - [\eta]$ of equally distributed equivalent incomes for different groups” (p.175).

$$c_e = \left(\sum_{g=1}^k \frac{n_g}{n} c_{eg}^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad (36)$$

where c_{eg} is the equally distributed equivalent income in group g . $\frac{n_g}{n}$ is the share of individuals in group g compared to the overall population n . Supposing only two relevant groups here (immigrants I and native-born population D), equation 36 can be reformulated as 37 and equation 35 as 38:

$$c_e = \left(p_D c_{eD}^{1-\eta} + \frac{p_I c_{eI}^{1-\nu} (1 - \eta)}{1 - \nu} \right)^{\frac{1}{1-\eta}} \quad (37)$$

$$V_i = (1 - \alpha)U(c_i) + \alpha \left[\frac{p_D c_{eD}^{1-\eta}}{1 - \eta} + \frac{p_I c_{eI}^{1-\nu}}{1 - \nu} \right] \quad (38)$$

From this follows:

$$V_i = (1 - \alpha)U(c_i) + \alpha U[\bar{c}(1 - (A_w + A_b + R))] \quad (39)$$

where A_w is within group inequality, A_b between group inequality and R a non-zero residual due to the non-additively decomposable nature of the Atkinson index (Das and Parikh, 1981, 176). The decomposed inequality in equation 39 is the result of the following rearrangement of the formula of Atkinson’s inequality index (as proposed by Das and Parikh):

$$\begin{aligned} A &= 1 - \frac{c_e}{\bar{c}} \Leftrightarrow c_e = \bar{c}(1 - A) \\ &= 1 - \frac{1}{\bar{c}} \left(\sum_{g=1}^k \frac{n_g}{n} c_{eg}^{1-\eta} \right)^{\frac{1}{1-\eta}} \\ &= 1 - \frac{1}{\bar{c}} \left(\sum_{g=1}^k p_g [\bar{c}_g (1 - A_g)]^{1-\eta} \right)^{\frac{1}{1-\eta}} \\ &= 1 - \left(\sum_{g=1}^k p_g \left(\frac{\bar{c}_g}{\bar{c}} \right)^{1-\eta} (1 - A_g)^{1-\eta} \right)^{\frac{1}{1-\eta}} \end{aligned} \quad (40)$$

Das and Parikh (1981) then define between-group inequality as the Atkinson inequality among the means of different groups, and within group inequality as the mean of order $1 - \eta$ of Atkinson inequality within each group:

$$A_b = 1 - \left(\sum_{g=1}^k p_g \left(\frac{\bar{c}_g}{\bar{c}} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad (41)$$

$$A_w = \left(\sum_{g=1}^k p_g \left(\frac{\bar{c}_g}{\bar{c}} \right)^{1-\eta} A_g^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad (42)$$

If the parameter used to weigh people's utility η is the same for both groups in the population, this decomposition would yield no different results. An increase in inequality due to a) changes in the population composition through p_g b) increase in between group inequality or c) increase in within-group population would all yield the same result in equation 39: higher support for redistribution with increasing inequality (this effect increasing with income). There are, however, arguably good grounds to suppose that *individual* inequality aversion might vary depending on which group we are looking at. There are two aspects that need to be considered here: a) how inequality averse the same individual is with respect to each group, i.e. what is the value judgement underlying the evaluation of the group-specific equally distributed equivalent income; and b) how an individual values the equally distributed equivalent income of one group compared to the other .

With respect to the first point, I assume that individuals are as inequality averse for members of 'their' group (in this case native-born) as they are risk-averse for themselves, therefore $\eta = \epsilon$ can be used to calculate c_e for native-born. For immigrant population however, δ is taken to denote 'out-group'-specific inequality aversion. Assuming $\delta \leq \eta$, the equally distributed equivalent income c_e for immigrants will be higher for the same distribution of income, hence the individual perceives less inequality.

$$c_{eD} = \left(\sum_{j=1}^{n_D} \frac{1}{n_D} c_{ej}^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad (43)$$

$$c_{eI} = \left(\sum_{j=1}^{n_I} \frac{1}{n_I} c_{ej}^{1-\delta} \right)^{\frac{1}{1-\delta}} \quad (44)$$

When comparing the two groups, however, it matters how much utility is gained from increasing c_e for one group compared to the other. If the shape of $U(c_e)$ is concave, only very low levels of c_e would lead to more support for redistribution. On the other hand, if it is steeper, the potential utility gain from increasing c_e is higher. Comparing immigrants and the native born population, I argue that increasing c_{eD} brings more utility than increasing c_{eI} —and therefore, $\nu \geq \eta$ (with $\nu = 1 - \delta$). As a consequence,

overall, between and within group inequality are:

$$A = 1 - \left[p_D \left(\frac{\bar{c}_D}{\bar{c}} \right)^{1-\eta} (1 - A_D)^{1-\eta} + p_I \left(\frac{\bar{c}_I}{\bar{c}} \right)^{1-\nu} (1 - A_I)^{1-\nu} \frac{1-\eta}{1-\nu} \right]^{\frac{1}{1-\eta}} \quad (45)$$

$$A_b = 1 - \left[p_D \left(\frac{\bar{c}_D}{\bar{c}} \right)^{1-\eta} + p_I \left(\frac{\bar{c}_I}{\bar{c}} \right)^{1-\nu} \right]^{\frac{1}{1-\eta}} \quad (46)$$

$$A_w = \left[p_D \left(\frac{\bar{c}_D}{\bar{c}} \right)^{1-\eta} A_D^{1-\eta} + p_I \left(\frac{\bar{c}_I}{\bar{c}} \right)^{1-\nu} A_I^{1-\nu} \right]^{\frac{1}{1-\eta}} \quad (47)$$

The main point stands: people will react differently to increases in inequality driven by immigrants (either more poor immigrants enter the country or immigrants within the country become poorer) than to inequality due to changes in the native born income distribution. This means that the effect of increases in inequality on redistribution preferences will depend on which component of inequality changes.

Between-group From equation 46 we can conclude that, since increasing average domestic income will always weigh more onto native born preferences, increases in inequality due to differences in group means (between-group inequality) will have little, if no impact on support for redistribution as a means to correct that difference if $\bar{c}_D > \bar{c}_I$. If on the other hand $\bar{c}_D \leq \bar{c}_I$, we would expect an increase in support for redistribution.

Within-group Firstly, as inequality aversion is assumed to be lower for immigrants, inequality A_I will be valued as lower than A_D at most levels of c_e .⁵ This means that the term in the second part of 47, will already be lower to begin with. Additionally, as less utility can be gained from decreasing inequality for that term overall because of ν , the same increases in inequality in each group will not result in the same desire to reduce those income differences.

Population weights The two points above show that the elements referring to the out-group in both equations 46 and 47 do not lead to similar changes in the individual *perception* of inequality, even if the ‘objective’ changes in the income distribution are the same. From this follows that if the share of immigrants p_I increases,⁶ the effect of overall inequality on support for redistribution will be reduced.

Taking the first order condition of equation 38 yields:

$$t^* = 1 - \frac{y_i}{\bar{y}} + \frac{\alpha}{1-\alpha} \left[p_D \left((1-t) - \frac{y_{eD}}{\bar{y}} \right) \frac{c_i^\epsilon}{c_{eD}^\epsilon} + p_I \left((1-t) - \frac{y_{eI}}{\bar{y}} \right) \frac{c_i^\epsilon}{c_{eI}^\nu} \right] \quad (48)$$

Depending on the difference between ϵ , η and ν , c_i , c_{eD} and c_{eI} will be weighed differently against each other. For a smaller η , the term in the nominator c_{eD}^η will be smaller, making $\frac{c_i^\epsilon}{c_{eD}^\eta}$ bigger overall and increasing with income. For a bigger ν , c_{eI}^ν will be comparatively bigger which leads to $\frac{c_i^\epsilon}{c_{eD}^\eta} > \frac{c_i^\epsilon}{c_{eI}^\nu}$. I therefore assume that $\eta \leq \epsilon < \nu$.

⁵Since c_{eI} is calculated with a smaller γ than ϵ , for an equal income distribution, c_{eD} will be lower than c_{eI} , except at extremely low levels of c_{eI}

⁶And $p_D = 1 - p_I$ decreases.

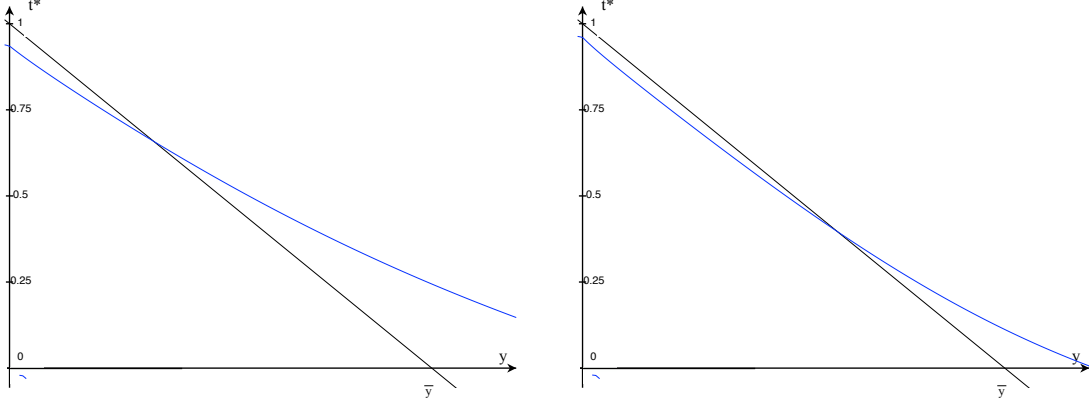


Figure A.1: Support for redistribution with altruism without (left) and with (right) heterogeneity

Beyond the formalisation of the second mechanism, the other contribution of this model is that altruism and resentment need not be treated as competing hypotheses, but as different parts of the same utility function. They are two different ways of considering the ‘other’ that are tendencies that may be present in all individuals, competing *within* individuals. Whether one impulse will dominate the other is, in turn, dependent on the individual material situation and the macro context of the income distribution. Combining both mechanisms, the integrated model is the following:

$$\begin{aligned}
 V_i &= (1 - \alpha - \beta)U(c_i) + \alpha U(c_e) + \beta G(p_j(c_i - \bar{c}_j)) \\
 &= (1 - \alpha - \beta) \frac{((1 - t)y_i + t\bar{y}(1 - \frac{1}{2}t))^{1-\epsilon}}{1 - \epsilon} + \alpha \frac{((1 - t)y_e + t\bar{y}(1 - \frac{1}{2}t))^{1-\eta}}{1 - \eta} + \beta \frac{((1 - t)p_j(y_i - \bar{y}_j))^{1-\gamma}}{1 - \gamma} \quad (49)
 \end{aligned}$$

Leaving aside for now the question of group heterogeneity, this incorporates the idea that people care (1) about themselves, (2) about society overall and (3) how their own situation compares to others. Taking the first order condition yields:

$$t^* = 1 - \frac{y_i}{\bar{y}} + \frac{\alpha}{1 - \alpha - \beta} \left((1 - t) - \frac{y_e}{\bar{y}} \right) \frac{c_i^\epsilon}{c_e^\eta} + \frac{\beta}{1 - \alpha - \beta} p_j \frac{\bar{y}_j - y_i}{\bar{y}} \frac{c_i^\epsilon}{(p_j(c_i - \bar{c}_j))^\gamma} \quad (50)$$

Figure A.2 illustrates the intuitions from equation 50 more concretely. The straight line is the function $t^*(y_i)$ for equation 3.3, where only material self-interest matters. In comparison, the other function is not linear: The lower level and concavity of the line at lower incomes reflects the effect of the resentment mechanism (fading with income). And as income increases, the altruism effect takes over and the income for which the preferred tax rate is zero is higher than what material self-interest would predict.

In Appendix A.4.1, I prove that the cross partial of the preferred tax rate with respect to individual income and macro inequality⁷ is positive overall. Again, in more formal terms, this means that $-\frac{\partial^2 t}{\partial y_i \partial y_e} > 0$. This is largely mirrors the proofs provided by Dimick et al. (2017), but extends the model by taking into account the relative income distance. The conclusions are the same: inequality matters more to the rich than to the poor and therefore support for redistribution is expected to be higher in high inequality contexts for the rich.

⁷Higher inequality means a lower equally distributed equalised income.



Figure A.2: Preferred tax rate as a function of income

A.4.1 Proof for $\frac{\partial^2 t}{\partial y_i \partial y_e} < 0$

Here I show how the effect of altruism depends on income but in the opposite way as relative satisfaction. As we are interested in the effect of increases in inequality (implying a lower c_e), we can reverse the sign in front of $\partial V'_i / \partial y_e$ in equation ???. In other words, a low equally distributed equivalised income should increase support for redistribution more for the rich than the poor. Showing that $\frac{\partial^2 t}{\partial y_i \partial y_e} < 0$ will provide sufficient proof for $-\frac{\partial^2 t}{\partial y_i \partial y_e} > 0$. Taking the cross-partial of equation ?? yields:⁸

$$\frac{\partial t}{\partial y_i} \left(\frac{\partial t}{\partial y_e} \right) = \frac{\frac{\partial V'_i}{\partial y_i \partial y_e} (-V''_i(t)) - V''_i(y_e) \frac{-\partial V'_i}{\partial y_i \partial t}}{(-V''_i(t))^2} \quad (52)$$

Factoring out $c_e^{-\eta} \alpha$ out of both $V''_i(c_e)$ and $V''_i(t)$, I can write equation 52 as:

$$\frac{\partial^2 t}{\partial y_i \partial y_e} = \frac{\frac{\partial A}{\partial y_i} (BC + DE + F) - A \left(\frac{\partial B}{\partial y_i} C + \frac{\partial C}{\partial y_i} B + \frac{\partial D}{\partial y_i} E + \frac{\partial E}{\partial y_i} D + \frac{\partial F}{\partial y_i} \right)}{(BC + DE + F)^2} \quad (53)$$

⁸Recalling from before, $\frac{dV_i}{dy_i} = \frac{\partial V'_i}{\partial y_i} + \frac{\partial V'_i}{\partial t} \frac{\partial t}{\partial y_i} + \frac{\partial V'_i}{\partial d_i} \frac{dd_i}{dy_i}$. Therefore,

$$\frac{\partial}{\partial y_i} \left(\frac{\partial t}{\partial y_e} \right) = \frac{\left(\frac{\partial^2 V'_i}{\partial y_i \partial y_e} + \frac{\partial^2 V'_i}{\partial t \partial y_e} \frac{dt}{dy_i} + \frac{\partial^2 V'_i}{\partial d_i \partial y_e} \frac{dd_i}{dy_i} \right) (-V''_i(t)) - V''_i(y_e) \left(\frac{\partial^2 (-V'_i)}{\partial y_i \partial t} + \frac{\partial^2 V'_i}{\partial t \partial t} \frac{dt}{dy_i} + \frac{\partial^2 V'_i}{\partial d_i \partial t} \frac{dd_i}{dy_i} \right)}{(-V''_i(t))^2} \quad (51)$$

Where:

$$A = -\frac{\eta(-y_e + \bar{y} - t\bar{y})(1-t)}{c_e} - 1 < 0 \quad (54)$$

$$B = \frac{1-\alpha-\beta}{\alpha} \left(\frac{c_i^{-\epsilon}}{c_e^{-\eta}} \right) > 0 \quad (55)$$

$$C = \frac{\epsilon(-y_i + \bar{y} - t\bar{y})^2}{c_i} + \bar{y} > 0 \quad (56)$$

$$D = \frac{\beta}{\alpha} \left(\frac{S_i^{-\gamma}}{c_e^{-\eta}} \right) > 0 \quad (57)$$

$$E = -\frac{\gamma(p_j(y_i - \bar{y}_j))}{1-t} > 0 \quad (58)$$

$$F = \frac{\eta(-y_e + \bar{y} - t\bar{y})^2}{c_e} + \bar{y} > 0 \quad (59)$$

Starting with A gives the following :

$$\begin{aligned} \frac{\partial A}{\partial y_i} &= \frac{\partial A}{\partial t} \frac{dt}{dy_i} \\ &= \left(-\frac{\eta(-\bar{y})(1-t) + \eta(-1)(-y_e + \bar{y} - t\bar{y})}{c_e} - \frac{\eta(-y_e + \bar{y} - t\bar{y})^2(1-t)}{c_e^2} \right) \frac{dt}{dy_i} \quad (60) \\ &= \eta c_e \left((1-t)\bar{y} + (-y_e + \bar{y} - t\bar{y}) - \frac{(1-t)(-y_e + \bar{y} - t\bar{y})^2}{c_e} \right) \frac{dt}{dy_i} \end{aligned}$$

If $y_i > y_e$, the tax rate will be lower than the one that maximises c_e , and then $-y_e + \bar{y} - t\bar{y} > 0$. Furthermore, c_e increases, leading to the negative fraction in the parentheses to go towards zero. Therefore, the overall term become negative because $\frac{dt}{dy_i} < 0$. If however the tax rate is higher than the one that maximises c_e , $-y_e + \bar{y} - t\bar{y} < 0$. But as $y_i \rightarrow y_e$, $-y_e + \bar{y} - t\bar{y} \rightarrow 0$, and the positive first term inside the round brackets dominates and the overall term is negative.

Now moving on to the second part in the nominator in equation 53: as $-A > 0$, the part inside the brackets in the second term should be negative, so that the cross-partial overall is negative.

$$\begin{aligned} \frac{\partial B}{\partial y_i} &= \frac{\partial B}{\partial y_i} + \frac{\partial B}{\partial t} \frac{dt}{dy_i} \\ &= \frac{1-\alpha-\beta}{\alpha} \left[\frac{(1-t)(-\epsilon)c_i^{-\epsilon-1}c_e^{-\eta}}{c_e^{-2\eta}} + \left(\frac{(-y_i + \bar{y} - t\bar{y})(-\epsilon)c_i^{-\epsilon-1}c_e^{-\eta}}{c_e^{-2\eta}} \right. \right. \\ &\quad \left. \left. - \frac{(-y_e + \bar{y} - t\bar{y})(-\eta)c_e^{-\eta-1}c_i^{-\epsilon}}{c_e^{-2\eta}} \right) \frac{dt}{dy_i} \right] \quad (61) \\ &= \frac{1-\alpha-\beta}{\alpha} \frac{c_e^\eta}{c_i^\epsilon} \epsilon \left[-\frac{(1-t)}{c_i} + \left(-\frac{(-y_i + \bar{y} - t\bar{y})}{c_i} + \frac{\eta/\epsilon(-y_e + \bar{y} - t\bar{y})}{c_e} \right) \frac{dt}{dy_i} \right] \end{aligned}$$

If $y_i > y_e$, the term inside the round brackets is positive and the term overall unambiguously negative. When $y_i < y_e$, the preferred tax rate will be lower than $1 - \frac{y_i}{\bar{y}}$, but higher than $1 - \frac{y_e}{\bar{y}}$, leading to the bracketed term to be negative. However, as $y_i \rightarrow y_e$, both $-y_i + \bar{y} - t\bar{y}$ and $-y_e + \bar{y} - t\bar{y} \rightarrow 0$ and the first, negative, term dominates. Therefore, $\frac{\partial B}{\partial y_i} < 0$.

Next we have:

$$\begin{aligned}
\frac{\partial C}{\partial y_i} &= \frac{\partial C}{\partial y_i} + \frac{\partial C}{\partial t} \frac{dt}{dy_i} \\
&= -\frac{2\epsilon(-y_i + \bar{y} - t\bar{y})}{c_i} - \frac{(1-t)\epsilon(-y_i + \bar{y} - t\bar{y})^2}{c_i^2} \\
&\quad + \left(-\frac{2\epsilon\bar{y}(-y_i + \bar{y} - t\bar{y})}{c_i} - \frac{\epsilon(-y_i + \bar{y} - t\bar{y})^3}{c_i^2} \right) \frac{dt}{dy_i} \\
&= \frac{\epsilon(-y_i + \bar{y} - t\bar{y})}{c_i} \left[-2 - \frac{(1-t)(-y_i + \bar{y} - t\bar{y})}{c_i} + \left(-2\bar{y} - \frac{(-y_i + \bar{y} - t\bar{y})^2}{c_i} \right) \frac{dt}{dy_i} \right] \quad (62)
\end{aligned}$$

The sign of this term depends on whether the tax rate is above or below the material-self interest model. Taking the case where $t < 1 - \frac{y_i}{\bar{y}}$, $-y_i + \bar{y} - t\bar{y}$ will be positive, which will make the two first terms negative and the two within the round brackets positive because $\frac{dt}{dy_i} < 0$. The overall term will remain positive as long as the latter two times $\frac{dt}{dy_i}$ are bigger than the former two. This is the case as long as the marginal change in tax rate dependent on income $\frac{dt}{dy_i}$ is $< -\frac{2c_i + (1-t)(-y_i + \bar{y} - t\bar{y})}{2c_i\bar{y} + (-y_i + \bar{y} - t\bar{y})^2}$. As $-y_i + \bar{y} - t\bar{y} \rightarrow 0$, this reduces to $\frac{dt}{dy_i} < -\frac{1}{\bar{y}}$, which will stop being true as income increases and the altruism effect pulls the preferred tax rate *above* material self-interest. I will come back to this when discussing $\frac{\partial^2 t}{\partial y_i \partial d_i}$.

Continuing,

$$\begin{aligned}
\frac{\partial D}{\partial y_i} &= \frac{\partial D}{\partial y_i} + \frac{\partial D}{\partial t} \frac{dt}{dy_i} + \frac{\partial D}{\partial d_i} \frac{dd_i}{dy_i} \\
&= \frac{\alpha S_i^\gamma}{\beta c_e^\eta} \left[\frac{\gamma(1-t)p_j}{S_i} + \left(\frac{(-\eta)(-y_e + \bar{y} - t\bar{y})}{c_e} - \frac{(-\gamma)(-y_i + \bar{y}_j)p_j}{S_i} \right) \frac{dt}{dy_i} + \frac{\gamma(1-t)}{S_i} \frac{dd_i}{dy_i} \right] \\
&= \frac{\alpha S_i^\gamma}{\beta c_e^\eta} \left[\frac{\gamma}{y_i - \bar{y}_j} + \left(-\frac{\eta(-y_e + \bar{y} - t\bar{y})}{c_e} - \frac{\gamma}{1-t} \right) \frac{dt}{dy_i} + \frac{\gamma}{(y_i - \bar{y}_j)p_j} \frac{dd_i}{dy_i} \right] \quad (63)
\end{aligned}$$

The first and third term inside the square brackets are clearly positive. The second term will be positive overall if the term inside the round brackets is negative. This is the case if $y_e < \frac{\gamma}{\eta}y_e + \frac{\gamma}{\eta}\frac{T(t)}{1-t} + (1-t)\bar{y}$, which means that γ has to be $> \eta \frac{y_e - (1-t)\bar{y}}{y_e + \frac{T(t)}{1-t}}$ for $\frac{\partial D}{\partial y_i}$ to be negative.

Next,

$$\begin{aligned}
\frac{\partial E}{\partial y_i} &= \frac{\partial E}{\partial y_i} + \frac{\partial E}{\partial t} \frac{dt}{dy_i} + \frac{\partial E}{\partial d_i} \frac{dd_i}{dy_i} \\
&= \frac{\gamma}{1-t} \left(p_j + \left[\frac{p_j(y_i - \bar{y}_j)}{1-t} \right] \frac{dt}{dy_i} + \left[1 \right] \frac{dd_i}{dy_i} \right) \quad (64)
\end{aligned}$$

This term is negative as long as $\frac{dt}{dy_i} < -\frac{2(1-t)}{y_i - \bar{y}_j}$. As $\frac{dt}{dy_i} \rightarrow 0$, the overall term tends to $2p_j$. I will come back to this and develop on it while showing that $\frac{\partial^2 t}{\partial y_i \partial d_i} > 0$ in equation 28.

Finally,

$$\begin{aligned}
\frac{\partial F}{\partial y_i} &= \frac{\partial F}{\partial t} \frac{dt}{dy_i} \\
&= \left[\frac{2\eta(-\bar{y})(-y_e + \bar{y} - t\bar{y})}{c_e} - \frac{\eta(-y_e + \bar{y} - t\bar{y})^3}{c_e^2} \right] \frac{dt}{dy_i} \\
&= - \left[\frac{2\eta\bar{y}(-y_e + \bar{y} - t\bar{y})}{c_e} + \frac{\eta(-y_e + \bar{y} - t\bar{y})^3}{c_e^2} \right] \frac{dt}{dy_i}
\end{aligned} \tag{65}$$

If $y_i > y_e$, the preferred tax rate will be smaller than the one that maximises c_e . Therefore, $y_e < \bar{y} - t\bar{y}$, and the two terms inside the square brackets will be positive, making the overall term positive. However, if $y_i < y_e$, the preferred tax rate will be bigger than the one maximising c_e and the overall term is negative. This illustrates the interplay between the altruism and resentment parts of the utility function. For a lower y_e (higher inequality), this term will become positive ‘sooner’ with rising income than if y_e was higher (lower inequality). In other words, the level of inequality will determine at what point the altruism effect will ‘take over’ and dominate the resentment effect.

As a next step, I now account for group heterogeneity in the combined model. This leads to the following utility function:⁹

$$V_i = (1 - \alpha - \beta)U(c_i) + \alpha \left[\frac{p_D c_{eD}^{1-\eta}}{1-\eta} + \frac{p_I c_{eI}^{1-\nu}}{1-\nu} \right] + \beta \left[p_D \frac{S_{iD}^{1-\gamma}}{1-\gamma} + p_I \frac{S_{iI}^{1-\nu}}{1-\nu} \right] \tag{66}$$

Both elements within the squared brackets are now the weighted sum of the respective type of social preference towards 1) the in-group (domestic population) and 2) the out-group (immigrants). After taking the first order condition of equation 66, the preferred tax rate is the following:

$$\begin{aligned}
t^* &= 1 - \frac{y_i}{\bar{y}} + \frac{\alpha}{1 - \alpha - \beta} \left[p_D \left((1 - t) - \frac{y_{eD}}{\bar{y}} \right) \frac{c_i^\epsilon}{c_{eD}^\eta} + p_I \left((1 - t) - \frac{y_{eI}}{\bar{y}} \right) \frac{c_i^\epsilon}{c_{eI}^\nu} \right] \\
&\quad + \frac{\beta}{1 - \alpha - \beta} \left[p_D \frac{\bar{y}_{jD} - y_i}{\bar{y}} p_{jD} \frac{c_i^\epsilon}{(p_{jD}(c_i - \bar{c}_{jD}))^\gamma} + p_I \frac{\bar{y}_{jI} - y_i}{\bar{y}} p_{jI} \frac{c_i^\epsilon}{(p_{jI}(c_i - \bar{c}_{jI}))^\nu} \right]
\end{aligned} \tag{67}$$

The implications of this equation can be summarised in Figure A.3, where I hold constant the level of inequality and assume micro-inequality to be a linearly increasing function for convenience. The red line represents the preferred tax rate as a function of income when there are no immigrants ($p_I = 0$). Conversely, the blue line shows what happens when p_I increases. As introducing heterogeneity does not change the implications of the proofs above, the claims made about the the curvature of the utility function apply here as well, as is also evidenced in Figure A.3. Disaggregating by mechanism, figures A.4a and A.4b show the effect of increasing p_I while holding the other mechanism constant. In Figure A.4a, when testing the effect an increasing share of immigrants through the altruism mechanism, I include only S_{iD} with $\gamma = \epsilon \frac{c_i - \bar{c}_j}{c_i}$ to hold the resentment effect constant over income. And in Figure A.4b, I include only c_e with the parameter $\eta = \epsilon = 0.5$ to show the change in the resentment mechanism on its own.

⁹Keeping in mind that $T(t) = t(\sigma_D \bar{y}_D + \sigma_I \bar{y}_I)(1 - \frac{1}{2}t)$.

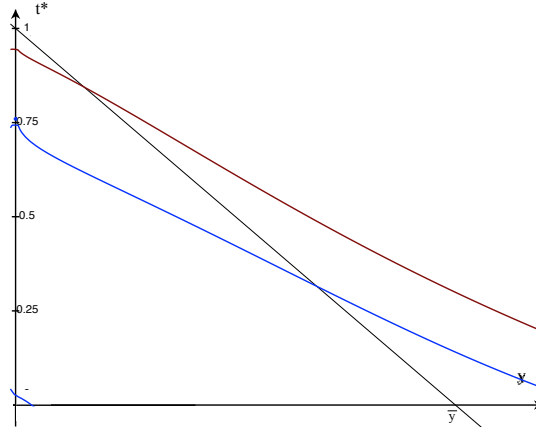
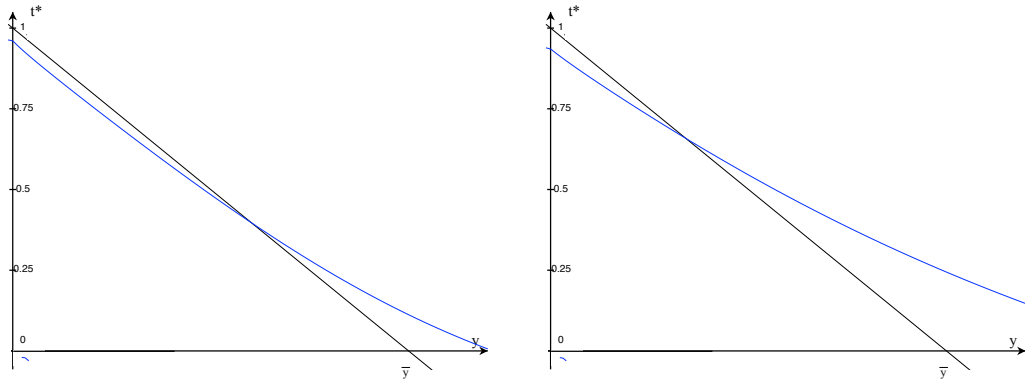
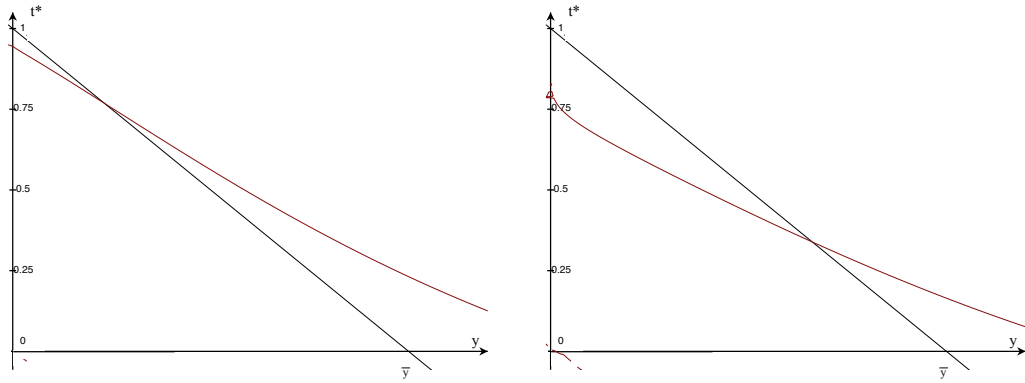


Figure A.3: Preferred tax rate with and without heterogeneity



(a) Effect of increased heterogeneity through altruism mechanism



(b) Effect of increased heterogeneity through resentment mechanism

Figure A.4: Mechanisms holding the other constant

Through the altruism mechanism, an increase in the share of immigrants leads to the preferred tax rate to follow the material self-interest predictions *more* closely. Conversely, through the resentment mechanism, the preferred tax rate will *diverge* from material self interest. Even more, these figures illustrate how—in the proposed model—heterogeneity channelled through the altruism mechanism only makes a difference for the rich and—conversely—how heterogeneity channelled through the resentment mechanism

moves and curbs the line for the poor.

On a micro-level, this would mean that immigration can reduce support for redistribution at all levels of income. Hence, one could question the need for this disaggregation into two different mechanisms. And yet, similar attitudinal shifts occurring within different societal groups do not necessarily have the same motives. Understanding these different specific logics still is valuable and could eventually inform which voter groups are more likely to be swayed by what kind of political discourse.

B Observational Evidence

B.1 Additional Descriptive Information

Table B.1: Weights

country	min	q25	median	q75	max	weighted n° of obs	unweighted n° of obs	population weight
AT	0.1	0.6	0.8	1.2	7.4	21328.4	21524	0.3
BE	0.0	0.8	0.9	1.1	6.3	19454.3	19625	0.5
CH	0.1	0.8	1.0	1.1	10.5	23189.7	23459	0.4
CZ	0.0	0.6	0.9	1.2	7.8	26844.4	26949	0.4
DE	0.0	0.6	1.0	1.2	4.1	33878.0	33930	2.5
DK	0.0	0.8	1.0	1.1	4.0	22155.6	22292	0.3
EE	0.4	0.8	1.0	1.2	2.1	15745.0	15812	0.1
ES	0.1	0.9	1.0	1.1	4.0	27456.2	27487	2.0
FI	0.5	0.8	1.0	1.1	2.9	24764.4	24973	0.2
FR	0.0	0.6	0.8	1.2	12.1	26026.6	26520	2.8
GB	0.0	0.6	0.9	1.2	6.0	26492.4	25737	2.3
GR	0.1	0.6	0.9	1.2	4.0	9371.3	9542	0.4
HU	0.0	0.7	0.9	1.2	4.2	18465.1	18431	0.5
IE	0.0	0.6	0.9	1.2	6.4	22843.9	23217	0.2
IS	0.3	1.0	1.0	1.0	2.6	7433.1	7470	0.0
IT	0.0	0.8	1.0	1.1	17.6	12275.0	12307	3.3
LT	0.0	0.6	1.0	1.1	5.0	14782.2	14589	0.1
LV	0.1	0.9	1.0	1.0	4.0	7926.4	7974	0.1
NL	0.2	0.7	0.9	1.2	8.5	21435.2	21779	0.7
NO	0.3	0.8	1.0	1.0	4.0	20482.6	20743	0.2
PL	0.3	0.9	1.0	1.1	2.3	17453.6	17438	1.9
PT	0.0	0.5	0.8	1.2	11.0	20222.0	20518	0.5
SE	0.1	0.9	1.0	1.0	4.0	22266.8	22178	0.4
SI	0.3	0.9	1.0	1.0	3.0	20611.8	20646	0.1
SK	0.0	0.7	1.0	1.2	4.9	16725.1	16733	0.3

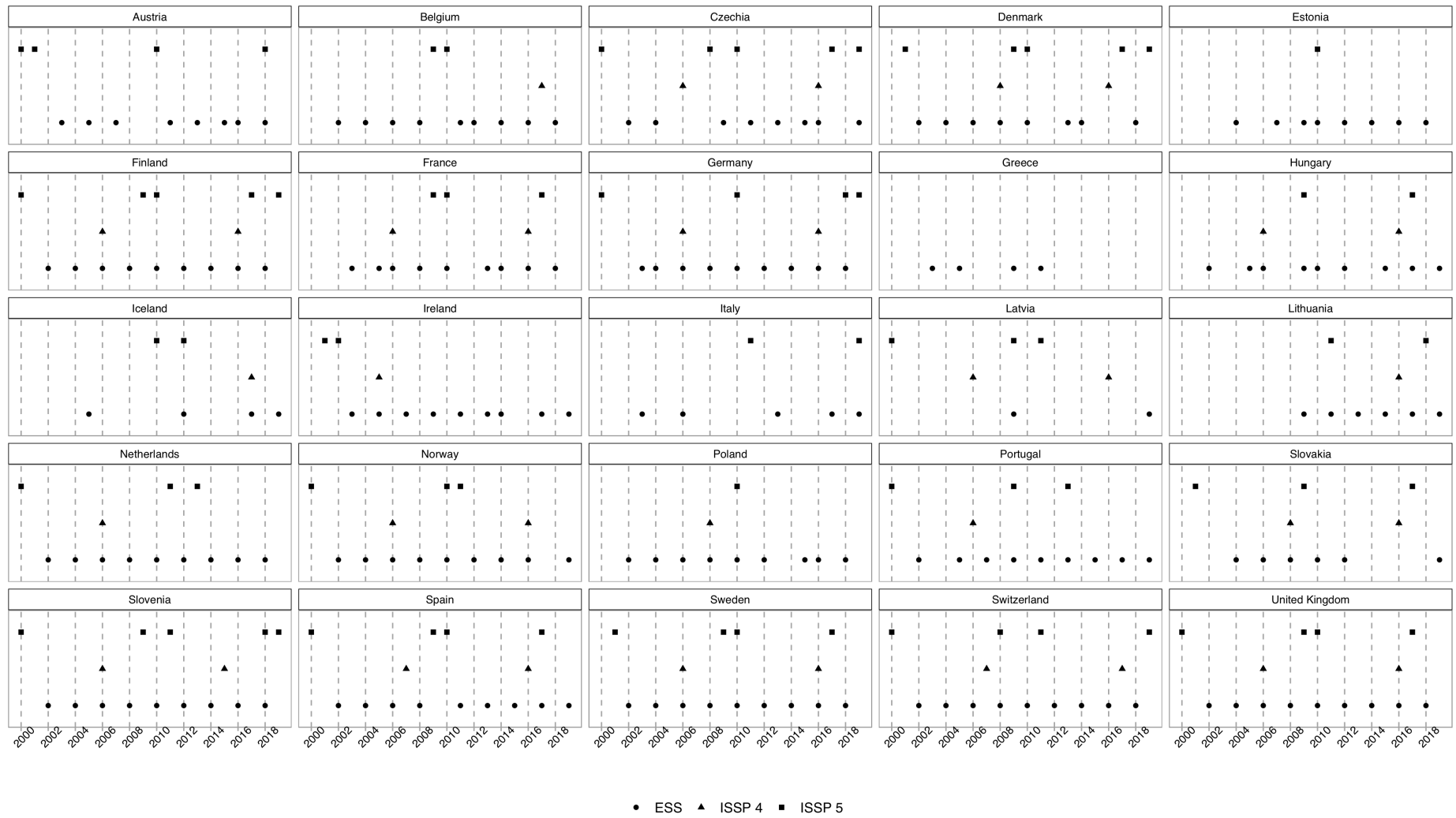


Figure B.1: Survey Item Coverage by Country

Table B.2: Support for Government Redistribution by Country - Binary Version

country	mean	sd	missing
AT	0.72	0.45	<i>3.3%</i>
BE	0.72	0.45	<i>1.24%</i>
CH	0.64	0.48	<i>1.88%</i>
CZ	0.58	0.49	<i>3.24%</i>
DE	0.69	0.46	<i>2.27%</i>
DK	0.46	0.50	<i>4.03%</i>
EE	0.75	0.43	<i>1.61%</i>
ES	0.83	0.38	<i>3.55%</i>
FI	0.75	0.44	<i>2.03%</i>
FR	0.77	0.42	<i>1.75%</i>
GB	0.62	0.49	<i>2.82%</i>
GR	0.89	0.31	<i>1.84%</i>
HU	0.85	0.35	<i>1.54%</i>
IE	0.75	0.43	<i>2.78%</i>
IS	0.74	0.44	<i>2.53%</i>
IT	0.83	0.38	<i>2.19%</i>
LT	0.88	0.33	<i>1.55%</i>
LV	0.80	0.40	<i>4.69%</i>
NL	0.59	0.49	<i>2.55%</i>
NO	0.63	0.48	<i>1.53%</i>
PL	0.78	0.41	<i>2.22%</i>
PT	0.89	0.31	<i>1.99%</i>
SE	0.66	0.47	<i>2.76%</i>
SI	0.86	0.34	<i>6.69%</i>
SK	0.77	0.42	<i>2.28%</i>
All	0.72	0.45	<i>2.61%</i>

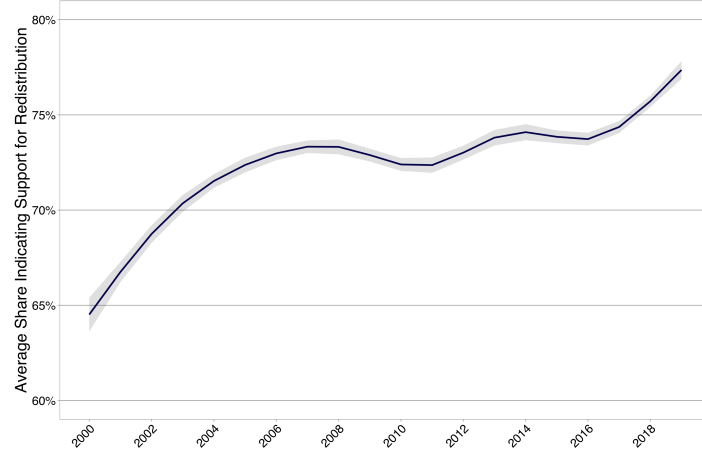
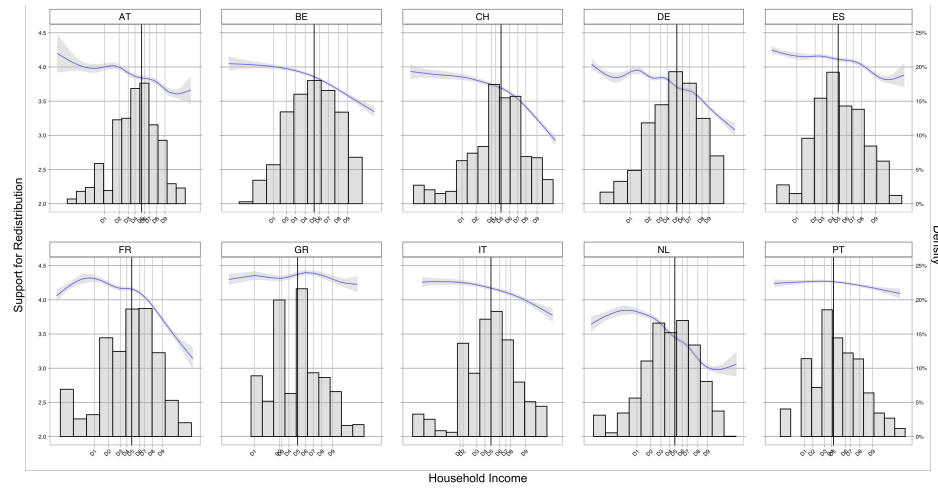


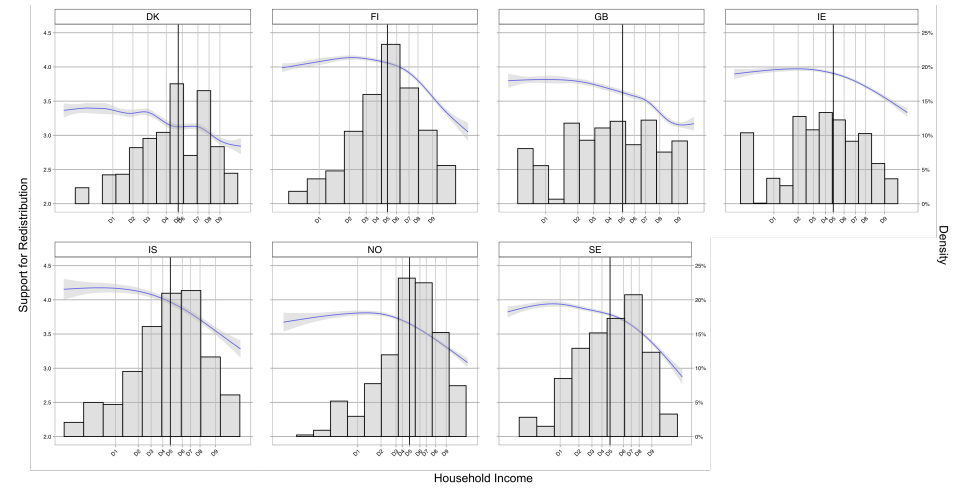
Figure B.2: Average Response in Data across Time - Binary Version
Estimated using a Generalised Logistic Additive Model (GAM) with a smooth term with cubic regression spline and a basis dimension $k = 8$ for time as only predictor. Sampling and population weights applied.

Table B.3: Equivalised Income by Country

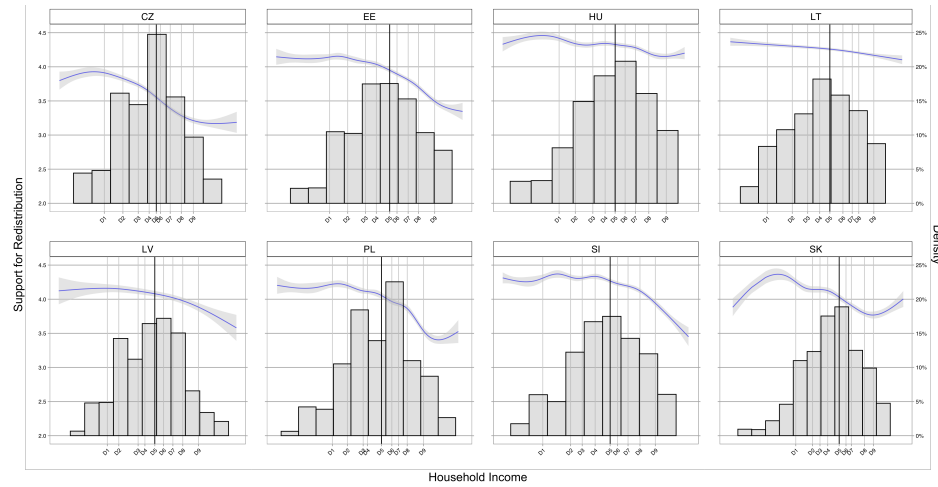
country	min	q25	median	q75	max	mean	sd	missing
AT	880	16970	22850	31800	209950	25610	15060	30%
BE	630	16870	22970	32070	232020	26010	14350	10%
CH	1130	27290	39230	56200	170120	43280	23420	20%
CZ	460	11980	16260	21870	332020	18620	12100	30%
DE	870	17570	24650	35600	256070	28740	17270	20%
DK	610	22090	34600	51250	179850	38330	21770	10%
EE	170	8000	12000	18610	113210	14760	10340	10%
ES	260	10620	16240	24610	187230	19370	13510	30%
FI	690	17760	25900	37170	630540	29680	22640	10%
FR	640	16710	24060	34300	451250	29240	25230	10%
GB	410	12520	22090	37120	172300	27290	19810	20%
GR	750	9400	14490	21160	211550	18130	15320	30%
HU	470	7660	10890	15240	159480	12440	8220	20%
IE	740	11560	18350	29250	165360	23010	16780	20%
IS	800	21080	30160	42160	488860	34160	22870	30%
IT	710	11830	17040	24580	165570	20560	14270	40%
LT	180	6210	9580	14420	87560	11000	6710	20%
LV	100	5090	7860	11990	83920	9730	7830	20%
NL	640	18040	25840	35600	217720	28710	16780	10%
NO	440	22220	31740	44570	716740	36410	29990	10%
PL	480	7380	11680	17100	336970	14120	12400	20%
PT	680	7580	12110	18000	270140	15700	14960	40%
SE	950	17400	25880	36850	481160	28930	18790	10%
SI	580	10030	15670	22160	206530	17440	11070	30%
SK	390	8820	13060	19430	373590	16670	15760	30%



(a) Bismarkian and Southern Welfare States



(b) Scandinavian and Anglo-Saxon Welfare States



(c) Eastern European Welfare States

Figure B.3: Average Response Depending on Income by Country

Note: Estimated using a Generalised Additive Model (GAM) separately for each country with the logarithm of income as a smooth predictor and years as random intercepts. Sampling weights applied.

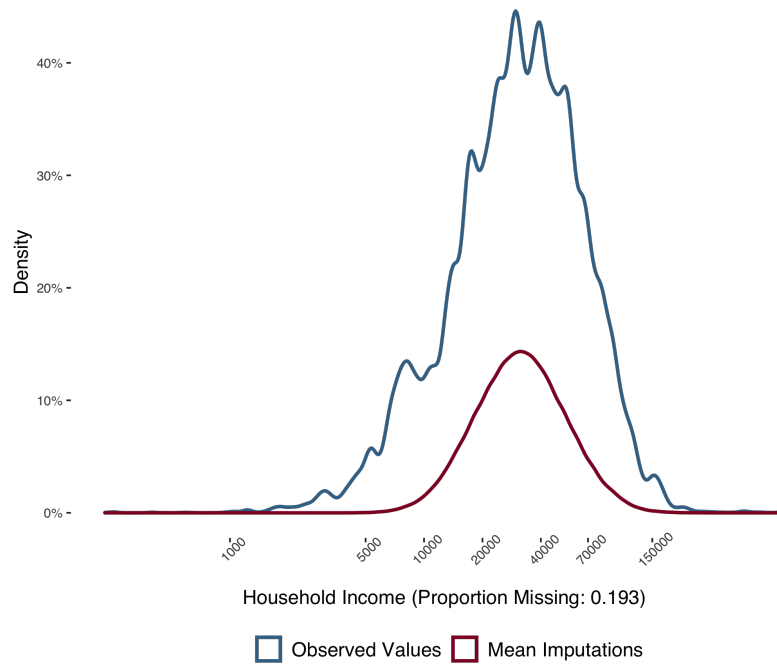


Figure B.4: Distribution of Household Income across Observed and Imputed Observations

Note: The imputations were performed by log-transforming household income before imputation and then exponentiating back. This is why the x-axis here is equally log-transformed.

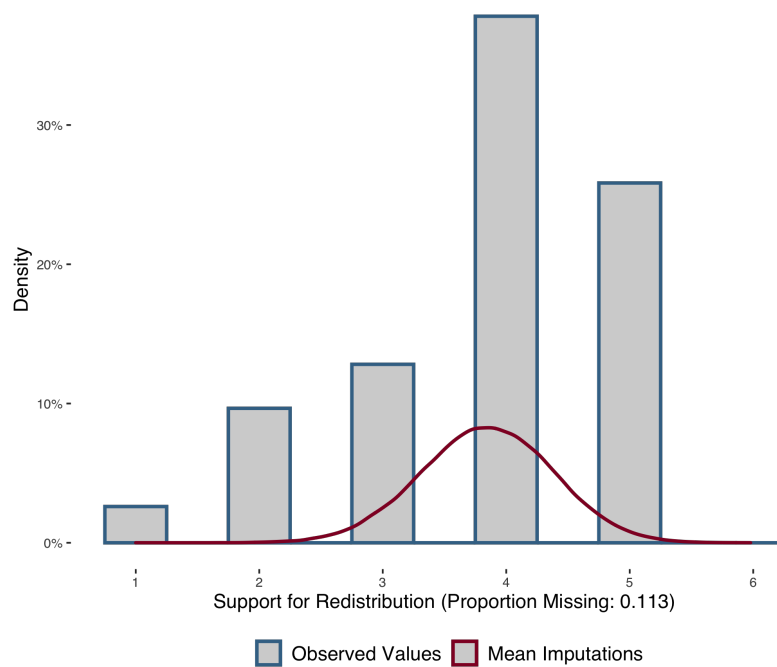


Figure B.5: Distribution of Support for Redistribution across Observed and Imputed Observations

B.2 Regression Results with Original Data

Table B.4: Multilevel Regression Results with Income Share of Bottom 50% - Original Data

	<i>Dependent variable:</i>											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Income Decile	-0.055*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.055*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.055*** (0.001)	-0.038*** (0.001)	-0.038*** (0.001)	-0.055*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)
$\Delta\%$ Foreign-born				-0.009* (0.005)	0.0004 (0.005)	0.010* (0.005)	-0.070*** (0.008)	-0.053*** (0.008)	-0.043*** (0.008)	-0.066*** (0.009)	-0.057*** (0.009)	-0.048*** (0.009)
Share Bottom 50%				-0.147*** (0.013)	-0.147*** (0.013)	-0.146*** (0.013)	-0.075*** (0.015)	-0.072*** (0.014)	-0.071*** (0.014)	-0.073*** (0.015)	-0.073*** (0.014)	-0.072*** (0.014)
Decile $\times \Delta\%$ FB							0.011*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
Decile $\times$ Share Bot.50%							-0.013*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)
$\Delta\%$ FB $\times$ Share Bot.50%										0.023 (0.015)	-0.013 (0.015)	-0.018 (0.015)
Decile $\times \Delta\%$ FB $\times$ Share Bot.50%										0.001 (0.002)	0.005*** (0.002)	0.005*** (0.002)
Intercept	4.195*** (0.061)	4.079*** (0.058)	3.895*** (0.165)	4.193*** (0.056)	4.079*** (0.053)	3.849*** (0.159)	4.192*** (0.056)	4.079*** (0.053)	3.849*** (0.159)	4.193*** (0.056)	4.079*** (0.054)	3.851*** (0.160)
Intercept Std. Error Country	0.298	0.282	0.233	0.275	0.26	0.225	0.275	0.26	0.224	0.276	0.26	0.225
Year	0.043	0.046	0.051	0.039	0.042	0.044	0.039	0.042	0.044	0.039	0.041	0.044
Survey Dummy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual-level Controls		✓	✓		✓	✓		✓	✓		✓	✓
Macro-level Controls			✓			✓			✓			✓
Observations	345,785	345,785	345,785	345,785	345,785	345,785	345,785	345,785	345,785	345,785	345,785	345,785
Log Likelihood	-508,591	-499,603	-499,588	-508,534	-499,542	-499,529	-508,4580	-499,466	-499,453	-508,461	-499,470	-499,458
AIC	1,017,195	999,243	999,224	1,017,085	999,124	999,111	1,016,936	998,975	998,961	1,016,946	998,989	998,976
BIC	1,017,259	999,436	999,482	1,017,171	999,340	999,391	1,017,043	999,212	999,262	1,017,075	999,247	999,299
Marginal R^2	0.023	0.071	0.106	0.027	0.077	0.107	0.028	0.078	0.108	0.0279	0.0780	0.1077

*p<0.1; **p<0.05; ***p<0.01

Note:

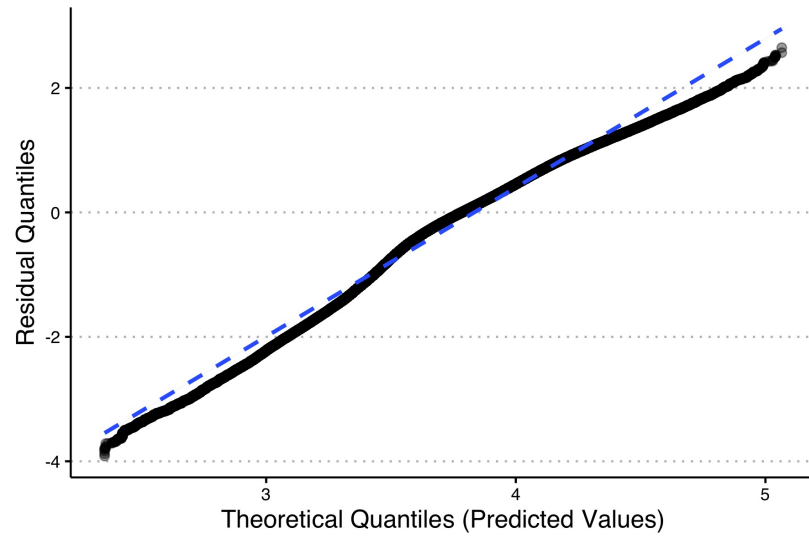
B.3 Regression Results with Income Threshold Ratio

Table B.5: Multilevel Regression Results with 50/10 and 90/50 Income Ratios - Original Data

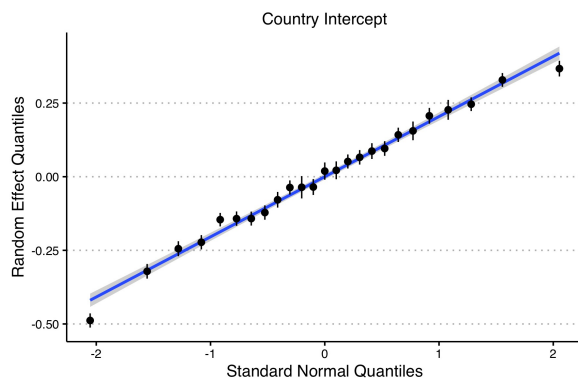
	<i>Dependent variable:</i>											
	Support for redistribution											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Income Decile	-0.056*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.056*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.056*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)	-0.056*** (0.001)	-0.039*** (0.001)	-0.039*** (0.001)
$\Delta\%$ Foreign-born				-0.007 (0.005)	0.002 (0.005)	0.014** (0.005)	-0.065*** (0.009)	-0.049*** (0.008)	-0.037*** (0.009)	-0.071*** (0.009)	-0.059*** (0.009)	-0.049*** (0.009)
50/10 Income Ratio				0.005 (0.008)	0.011 (0.007)	0.012 (0.008)	0.014 (0.012)	0.034*** (0.012)	0.034*** (0.012)	0.015 (0.012)	0.036*** (0.012)	0.037*** (0.012)
90/50 Income Ratio				0.038*** (0.012)	0.033*** (0.012)	0.022* (0.012)	-0.036*** (0.015)	-0.054*** (0.015)	-0.066*** (0.015)	-0.036*** (0.015)	-0.052*** (0.015)	-0.063*** (0.015)
50/10 Income Ratio $\times$ 90/50 Income Ratio				0.084*** (0.011)	0.084*** (0.011)	0.096*** (0.011)	0.083*** (0.011)	0.083*** (0.011)	0.096*** (0.011)	0.084*** (0.011)	0.088*** (0.011)	0.104*** (0.011)
Decile $\times$ $\Delta\%$ FB							0.011*** (0.001)	0.009*** (0.001)	0.009*** (0.001)	0.012*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
Decile $\times$ 50/10 Ratio							-0.002 (0.002)	-0.004*** (0.002)	-0.004*** (0.002)	-0.002 (0.002)	-0.004*** (0.002)	-0.004*** (0.002)
Decile $\times$ 90/50 Ratio							0.013*** (0.002)	0.016*** (0.002)	0.016*** (0.002)	0.013*** (0.002)	0.016*** (0.002)	0.016*** (0.002)
$\Delta\%$ FB $\times$ 50/10 Ratio										0.025* (0.015)	0.044*** (0.014)	0.051*** (0.014)
Decile $\times$ $\Delta\%$ FB $\times$ 50/10 Ratio										-0.004** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)
Constant	4.180*** (0.060)	4.061*** (0.057)	3.904*** (0.165)	4.164*** (0.058)	4.047*** (0.056)	3.880*** (0.167)	4.164*** (0.058)	4.047*** (0.056)	3.879*** (0.167)	4.164*** (0.058)	4.047*** (0.056)	3.877*** (0.168)
Intercept Std. Error Country Year	0.287 0.045	0.269 0.048	0.232 0.051	0.281 0.045	0.265 0.048	0.236 0.052	0.281 0.045	0.265 0.048	0.236 0.052	0.281 0.045	0.265 0.048	0.237 0.053
Survey Dummy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual-level Controls		✓	✓		✓	✓		✓	✓		✓	✓
Macro-level Controls			✓			✓			✓			✓
Observations	339,429	339,429	339,429	339,429	339,429	339,429	339,429	339,429	339,429	339,429	339,429	339,429
Log Likelihood	-500.026	-491.058	-491.046	-499.998	-491.026	-491.004	-499.941	-490.965	-490.942	-499.948	-490.969	-490.945
AIC	1,000.065	982.152	982.141	1,000.016	982.097	982.063	999.908	981.980	981.946	999.926	981.992	981.955
BIC	1,000.129	982.345	982.398	1,000.123	982.333	982.364	1,000.047	982.248	982.279	1,000.087	982.282	982.309
Marginal R^2	0.0231	0.0728	0.1019	0.0240	0.0743	0.1026	0.0244	0.0746	0.1031	0.0244	0.0748	0.1031

*p<0.1; **p<0.05; ***p<0.01

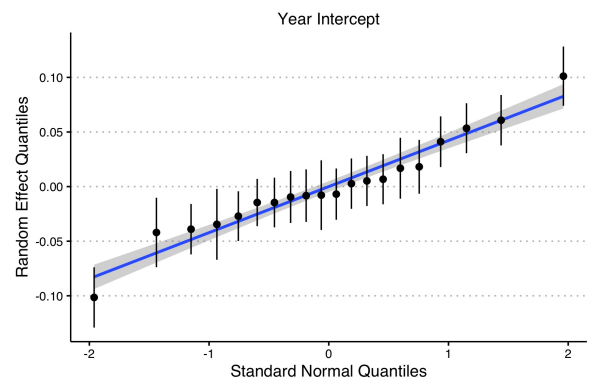
Note:



(a) QQ-plot of Residuals



(b) QQ-plot of Country Random Effect



(c) QQ-plot of Year Random Effect

Figure B.6: Diagnostic Plots for Model 9

B.4 Robustness Checks I: Binary Dependent Variable

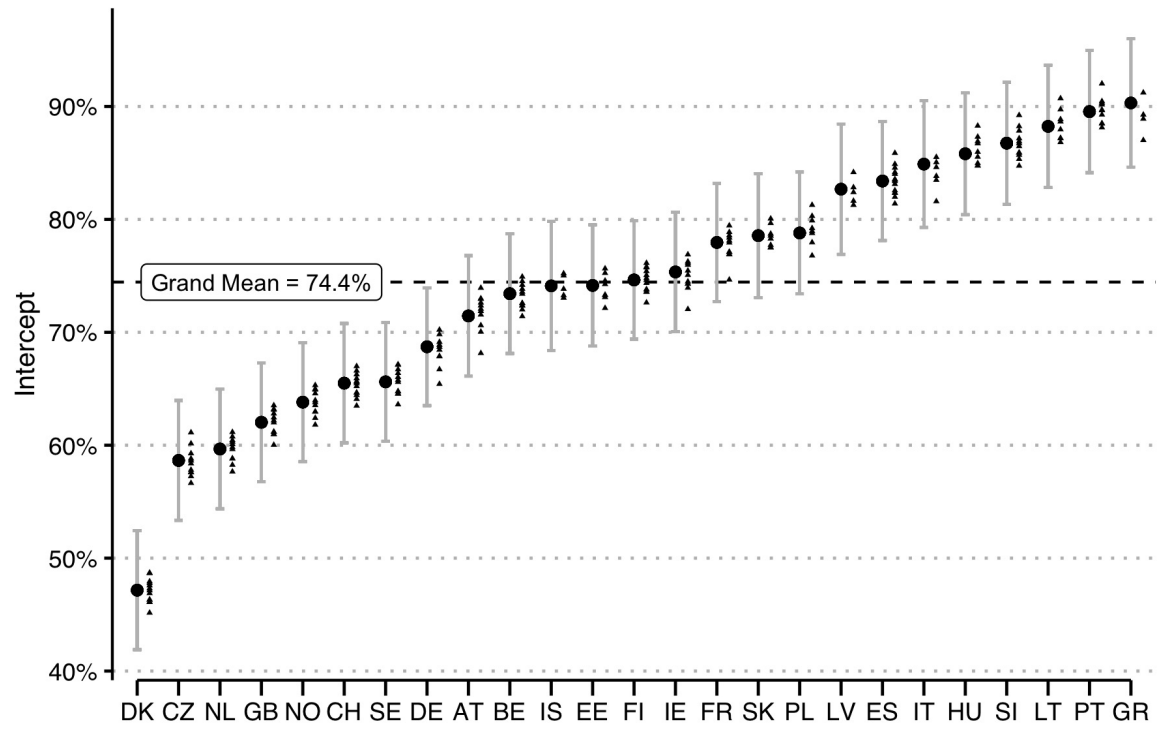
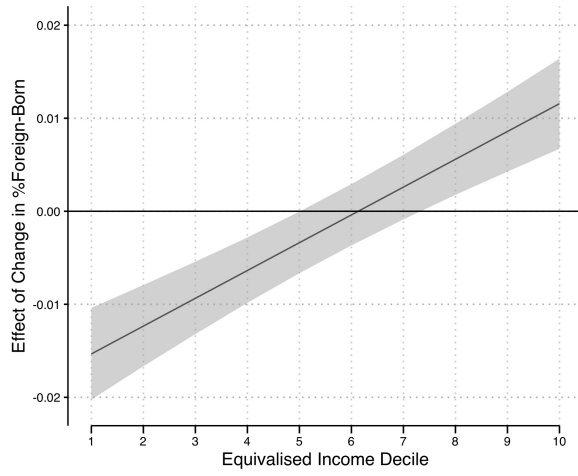
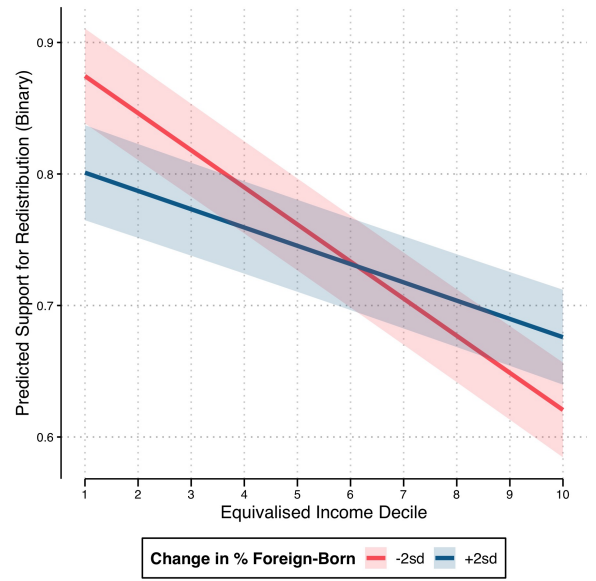


Figure B.7: Country and Country-Year Random Intercepts from Null-Model with Binary DV

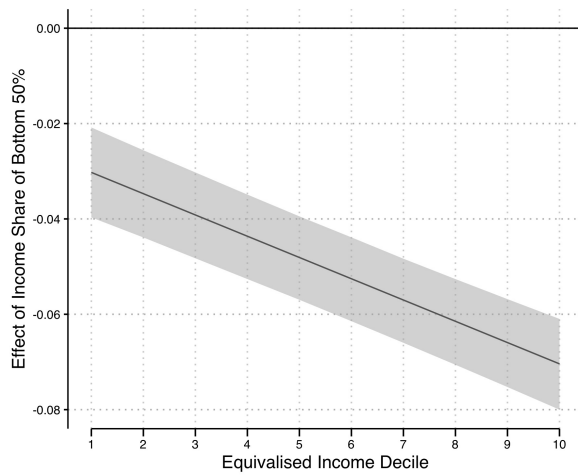


(a) Marginal Effect

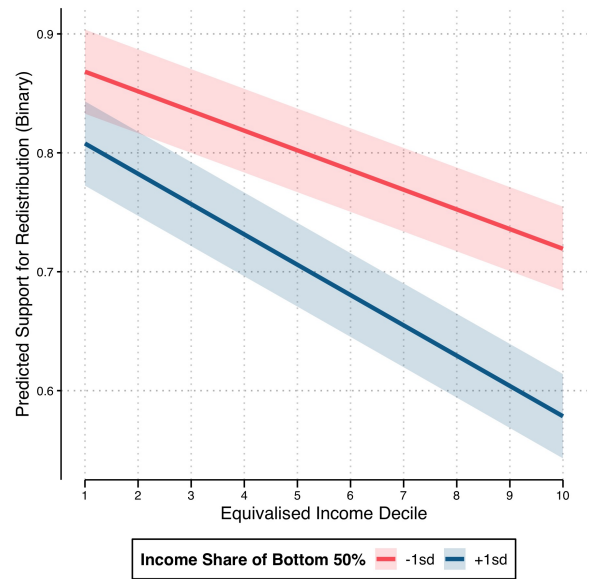


(b) Predicted Outcomes

Figure B.8: Interaction of Income and $\Delta\%$ Foreign-Born (Binary DV)



(a) Marginal Effect



(b) Predicted Outcomes

Figure B.9: Interaction of Income and Income Share of Bottom 50% (Binary DV)

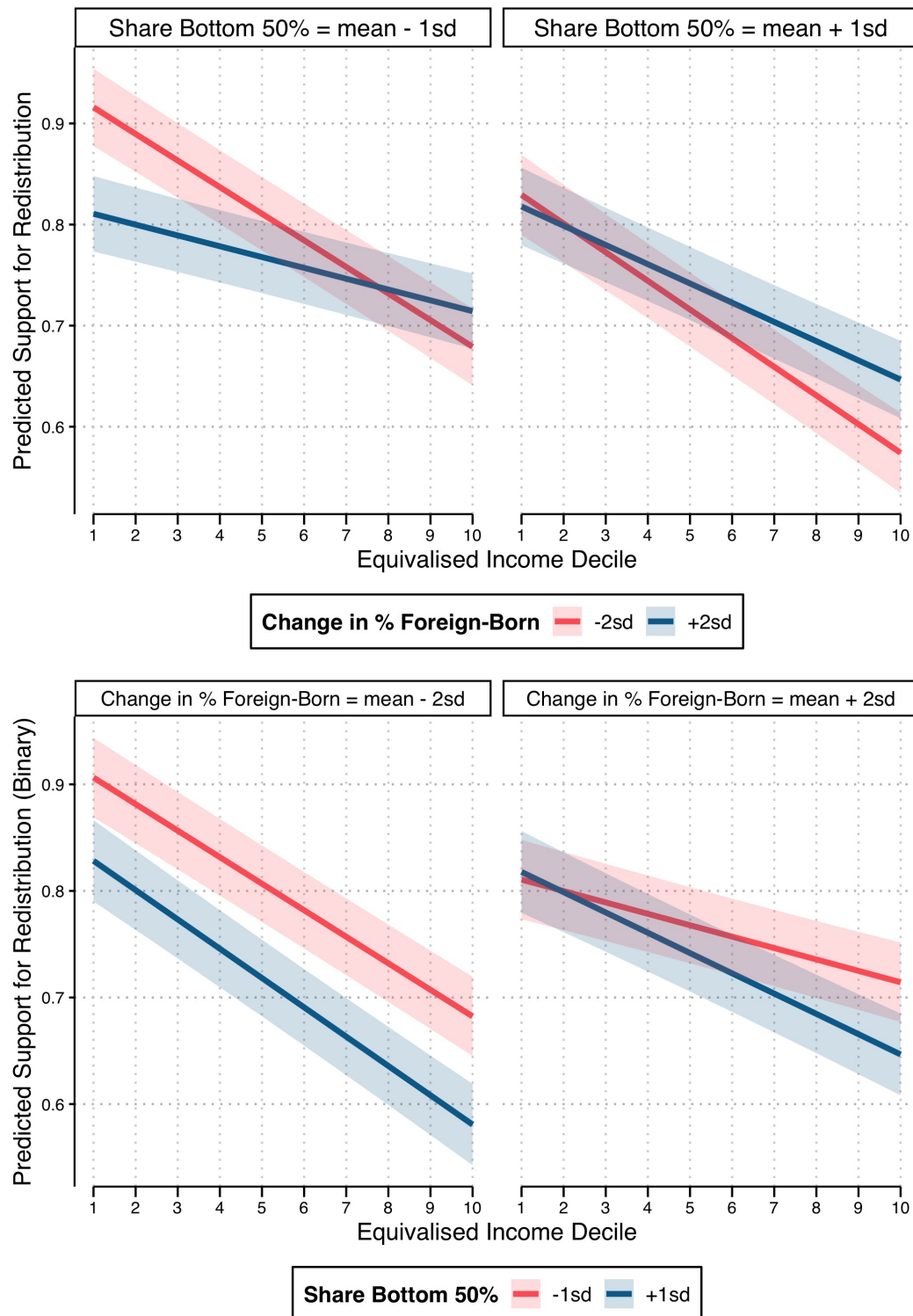


Figure B.10: Predicted Outcomes with Three-Way Interaction (Binary DV)

Table B.6: Multilevel Regression Results - Binary DV- Imputed Data

	<i>Dependent variable:</i>								
	Support for redistribution (Binary Version)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income Decile	-0.02*** (0.000)	-0.015*** (0.000)	-0.015*** (0.000)	-0.02*** (0.000)	-0.015*** (0.000)	-0.015*** (0.000)	-0.02*** (0.000)	-0.015*** (0.000)	-0.015*** (0.000)
$\Delta\%$ Foreign-born				-0.001 (0.002)	0.001 (0.002)	0.003 (0.002)	-0.018*** (0.003)	-0.014*** (0.003)	-0.012*** (0.003)
Share Bottom 50%				-0.04*** (0.005)	-0.041*** (0.005)	-0.042*** (0.005)	-0.014*** (0.005)	-0.015*** (0.005)	-0.017*** (0.005)
Decile $\times$ $\Delta\%$ FB							0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Decile $\times$ Share Bot.50%							-0.005*** (0.000)	-0.005*** (0.000)	-0.005*** (0.000)
Intercept	0.843*** (0.022)	0.8*** (0.021)	0.755*** (0.059)	0.843*** (0.02)	0.8*** (0.019)	0.742*** (0.056)	0.843*** (0.02)	0.8*** (0.019)	0.742*** (0.056)
Intercept Std. Error	0.109	0.103	0.083	0.1	0.095	0.079	0.1	0.095	0.079
Country									
Year	0.013	0.014	0.014	0.013	0.013	0.013	0.013	0.013	0.013
Survey Dummy	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual-level Controls		✓	✓		✓	✓		✓	✓
Macro-level Controls			✓			✓			✓
Observations	482,055	482,055	482,055	482,055	482,055	482,055	482,055	482,055	482,055
Log Likelihood	-301,444	-292,822	-292,833	-301,419	-292,793	-292,800	-301,352	-292,730	-292,738
AIC	602,900	585,680	585,713	602,853	585,626	585,653	602,725	585,505	585,532
BIC	602,966	585,880	585,979	602,942	585,847	585,941	602,836	585,749	585,842
Marginal R^2	0.017	0.052	0.079	0.019	0.055	0.079	0.02	0.055	0.079

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

Table B.7: Multilevel Regression with Three-Way Interactions - Binary DV - Imputed Data

		<i>Dependent variable:</i>		
		Support for redistribution		
		(10)	(11)	(12)
Income Decile		−0.02*** (0.000)	−0.015*** (0.000)	−0.015*** (0.000)
$\Delta\%$ Foreign-born		−0.013*** (0.003)	−0.012*** (0.003)	−0.01*** (0.003)
Share Bottom 50%		−0.013** (0.005)	−0.015*** (0.005)	−0.016*** (0.005)
Decile $\times$ $\Delta\%$ FB		0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Decile $\times$ Share Bot.50%		−0.005*** (0.000)	−0.005*** (0.000)	−0.005*** (0.000)
$\Delta\%$ FB $\times$ Share Bot.50%		0.019*** (0.006)	0.008 (0.006)	0.008 (0.006)
Decile $\times$ $\Delta\%$ FB $\times$ Share Bot.50%		−0.002** (0.001)	−0.001 (0.001)	−0.001 (0.001)
Intercept		0.843*** (0.02)	0.8*** (0.019)	0.742*** (0.056)
Intercept Std. Error	Country	0.10	0.095	0.079
	Year	0.013	0.013	0.013
Survey Dummy		✓	✓	✓
Individual-level Controls			✓	✓
Macro-level Controls				✓
Observations		482,055	482,055	482,055
Log Likelihood		−301,357	−292,740	−292,748
AIC		602,738	585,528	585,555
BIC		602,871	585,794	585,888
Marginal R^2		0.02	0.055	0.079

Note:

*p<0.1; **p<0.05; ***p<0.01

B.5 Robustness Checks II

B.5.1 Pre-Tax Palma Ratio as Independent Variable

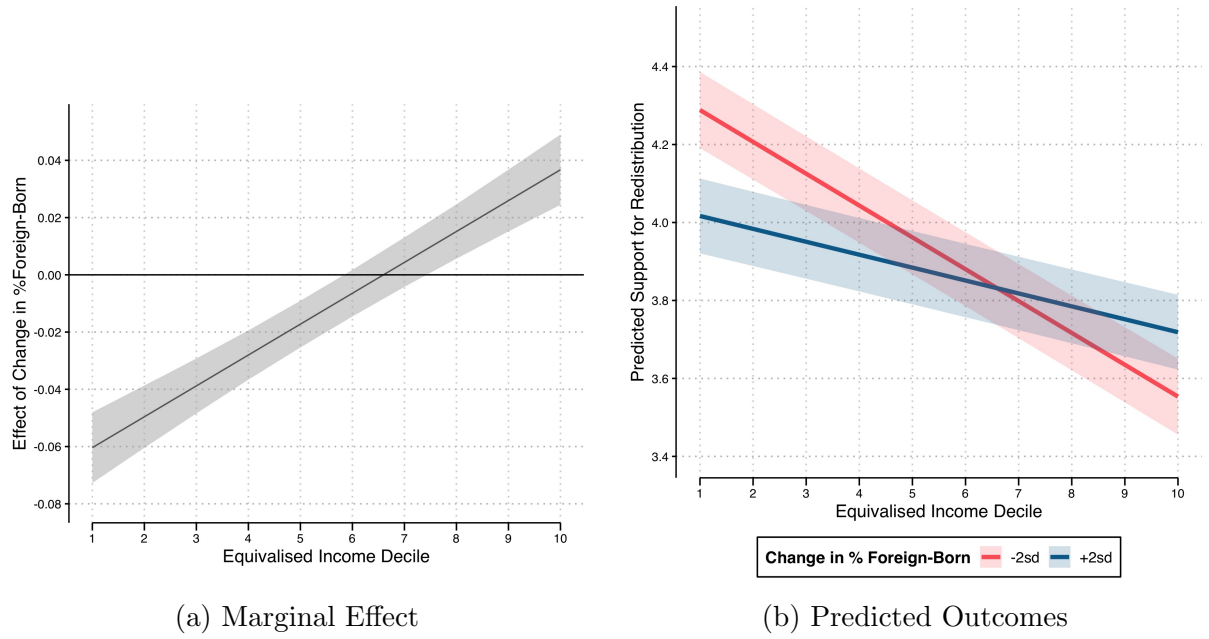


Figure B.11: Interaction of Income and $\Delta\%$ Foreign-Born

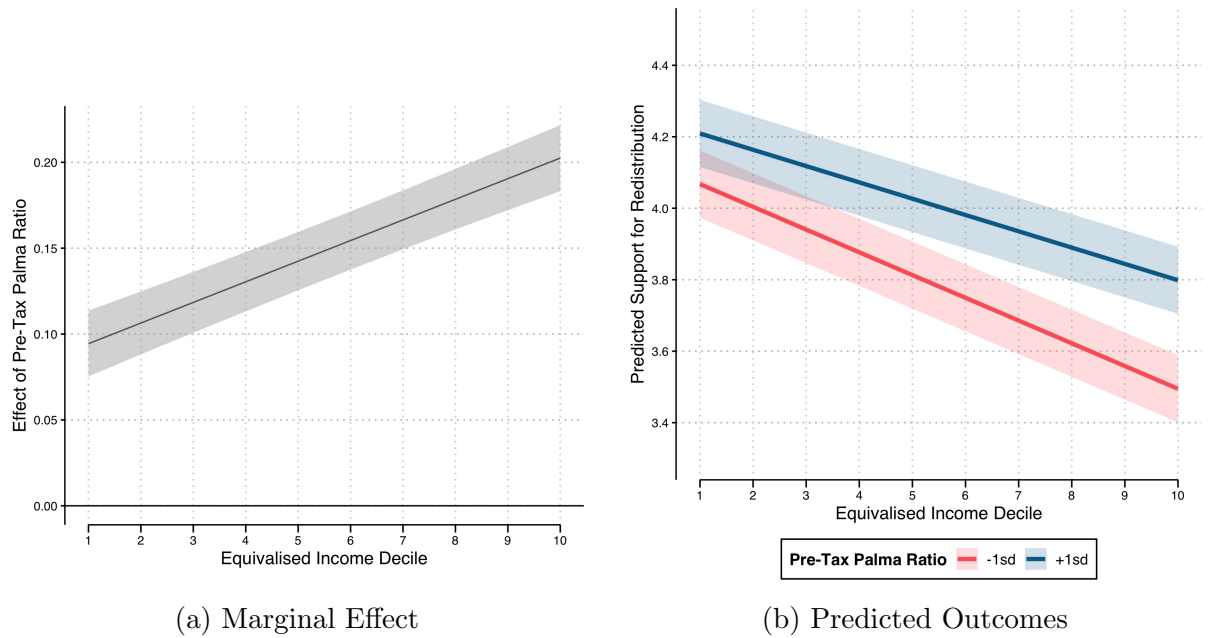


Figure B.12: Interaction of Income and Palma Ratio

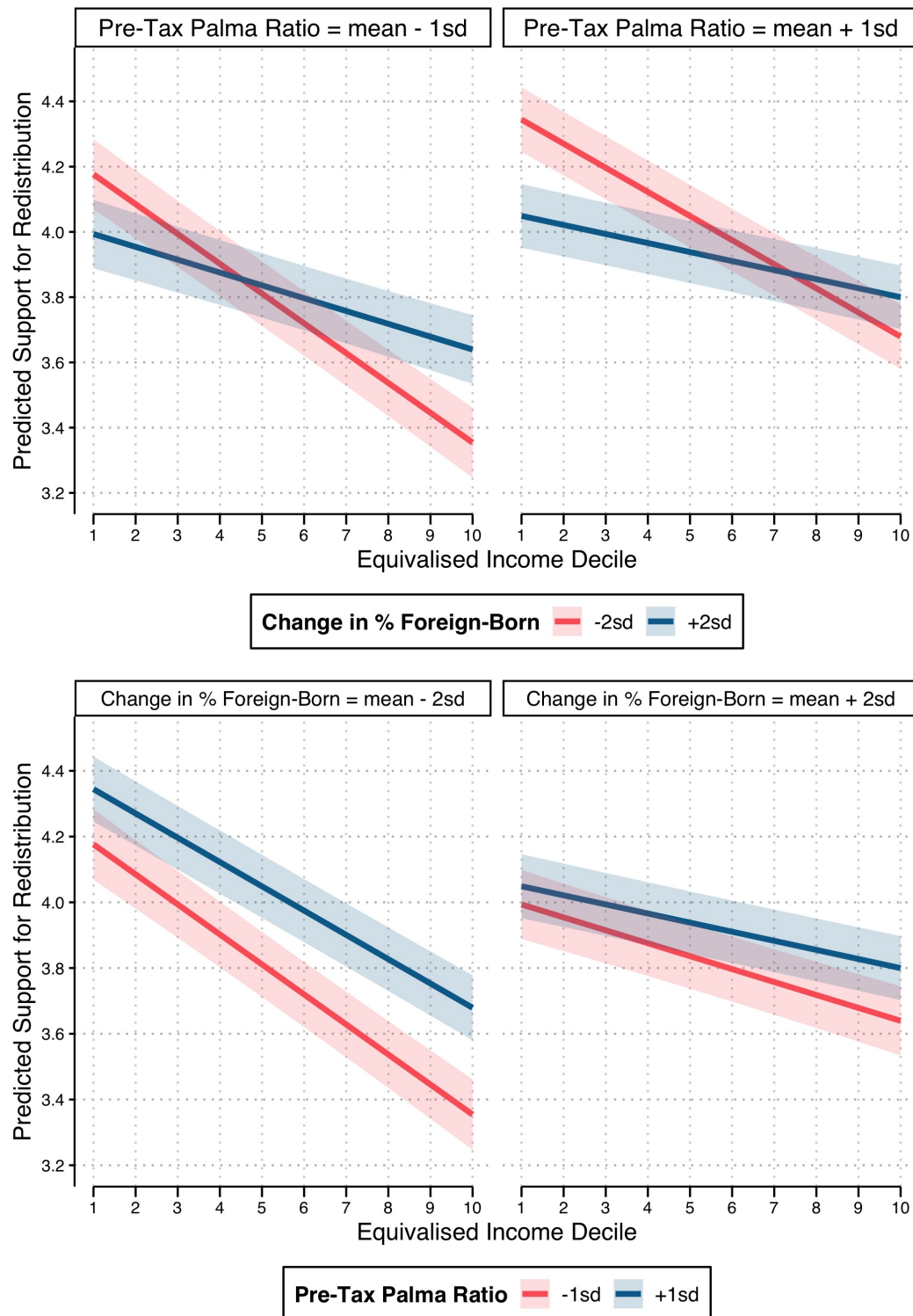


Figure B.13: Predicted Outcomes with Three-Way Interaction

B.5.2 Medium Term Change in % Foreign-Born as Independent Variable

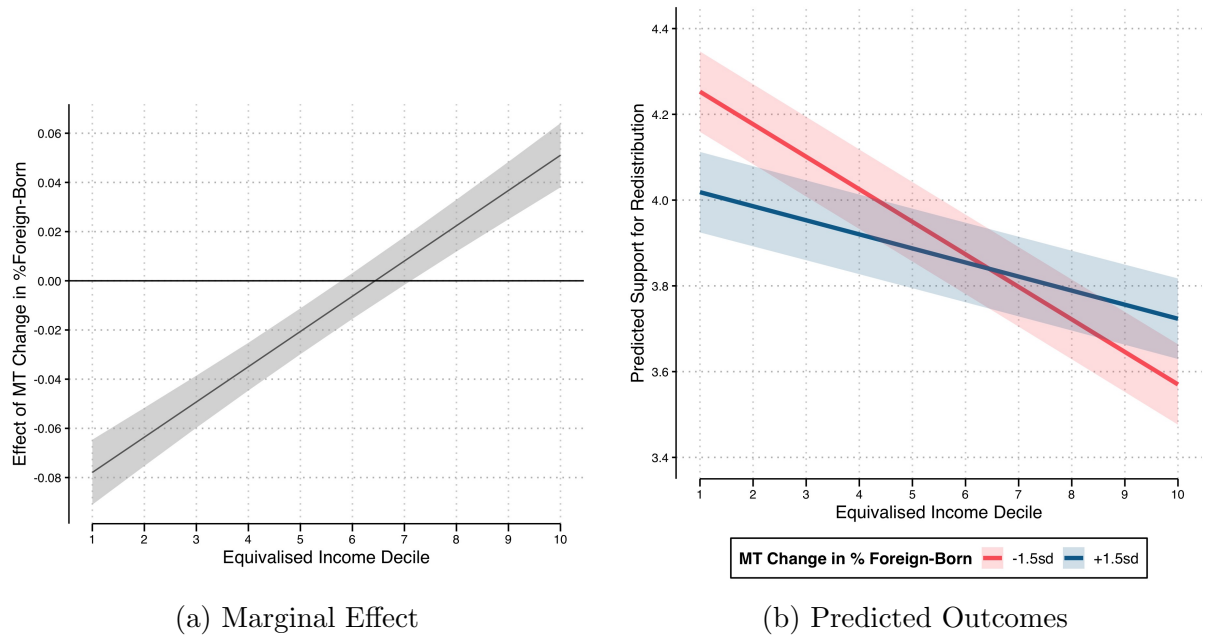


Figure B.14: Interaction of Income and Medium Term $\Delta\%$ Foreign-Born

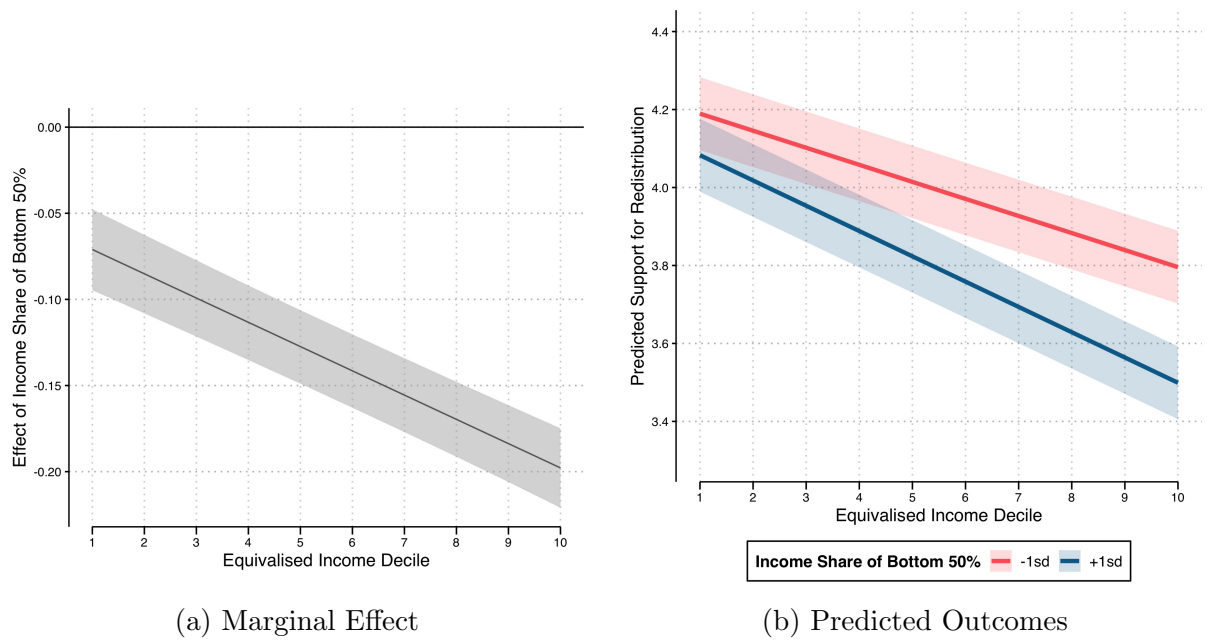


Figure B.15: Interaction of Income and Palma Ratio

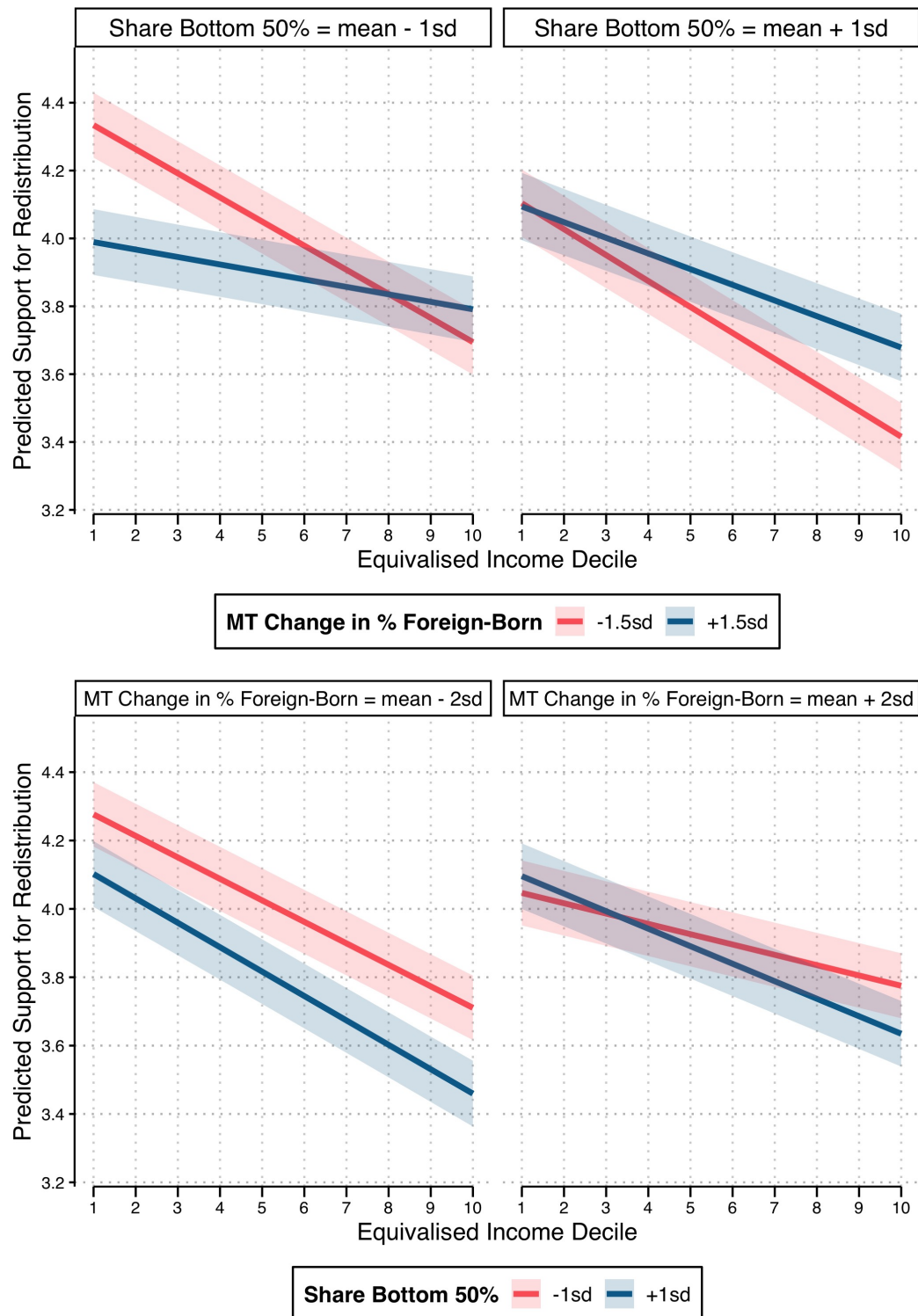


Figure B.16: Predicted Outcomes with Three-Way Interaction

B.6 Robustness Checks III: Fixed Effects Models

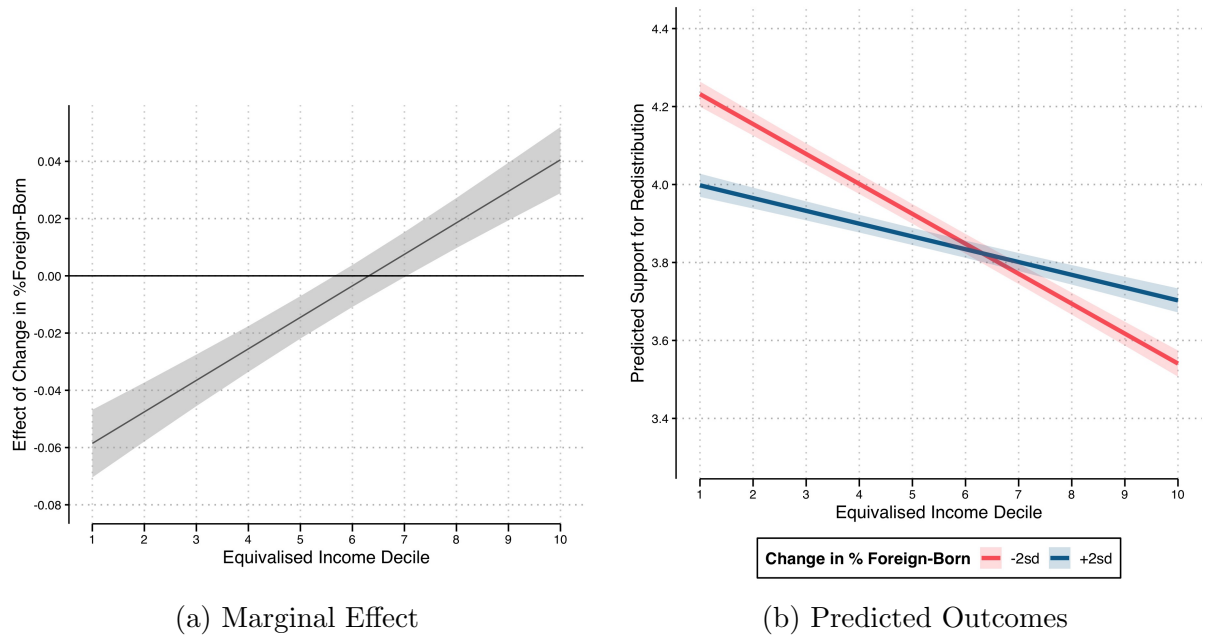


Figure B.17: Interaction of Income and Short Term $\Delta\%$ Foreign-Born - Fixed Effect Model

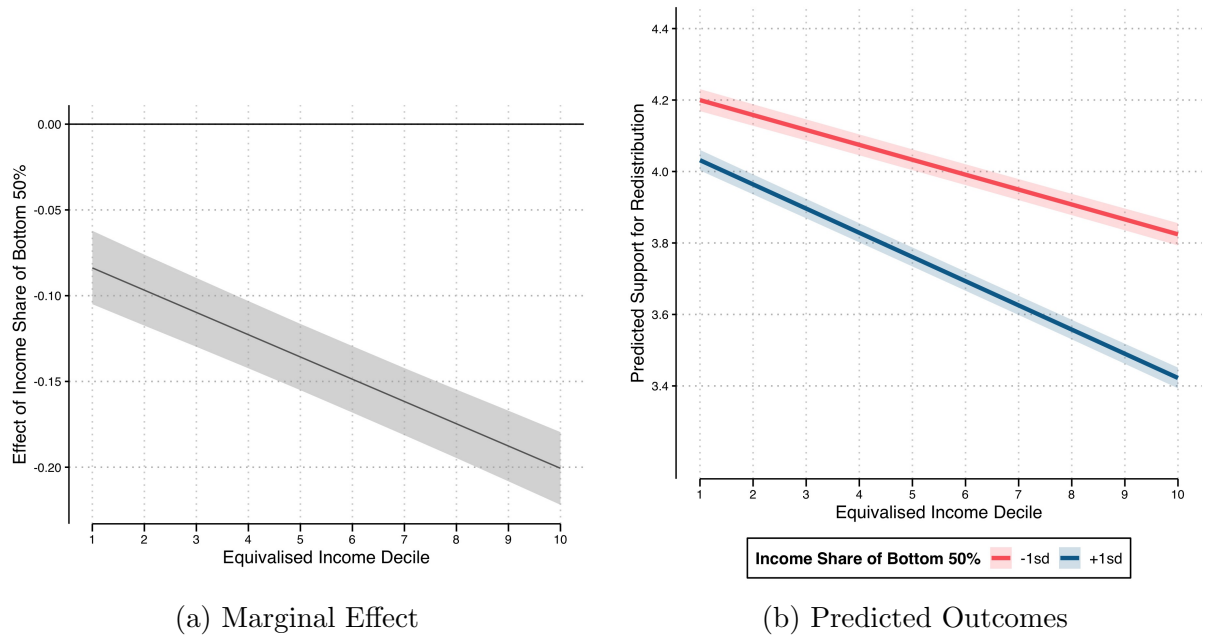


Figure B.18: Interaction of Income and Share Bottom 50% - Fixed Effect Model

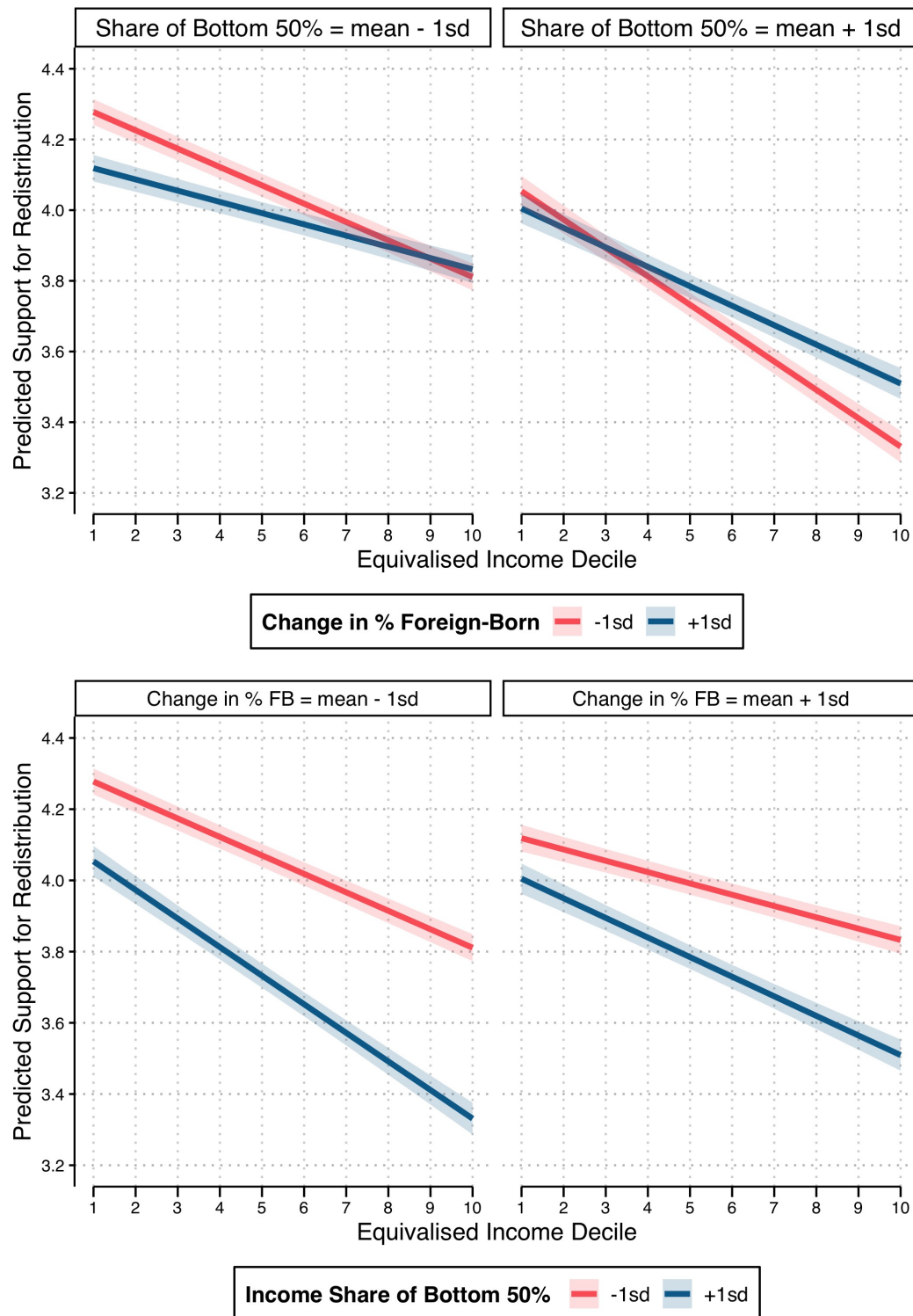
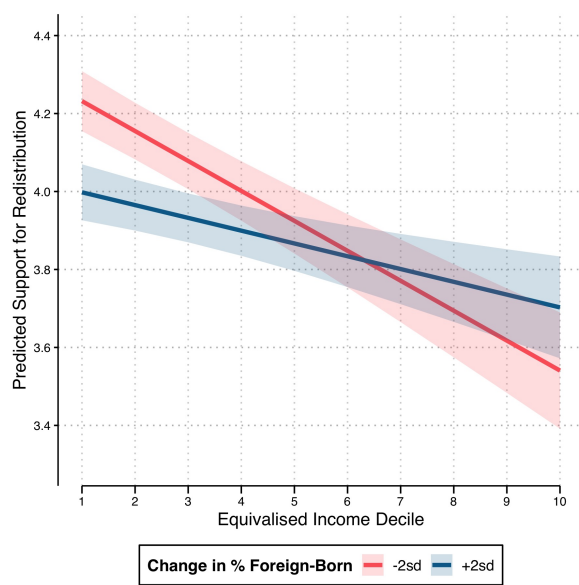
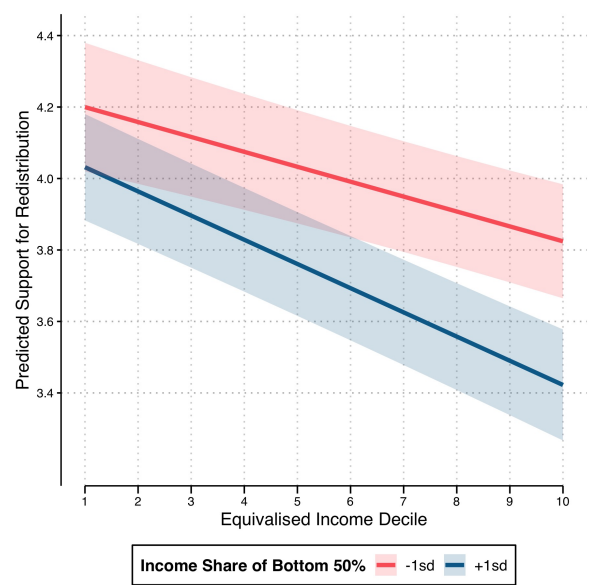


Figure B.19: Predicted Outcomes with Three-Way Interaction - Fixed Effect Model



(a)



(b)

Figure B.20: Predicted Outcomes with Two-Way Interactions- Fixed Effect Model with Clustered SE

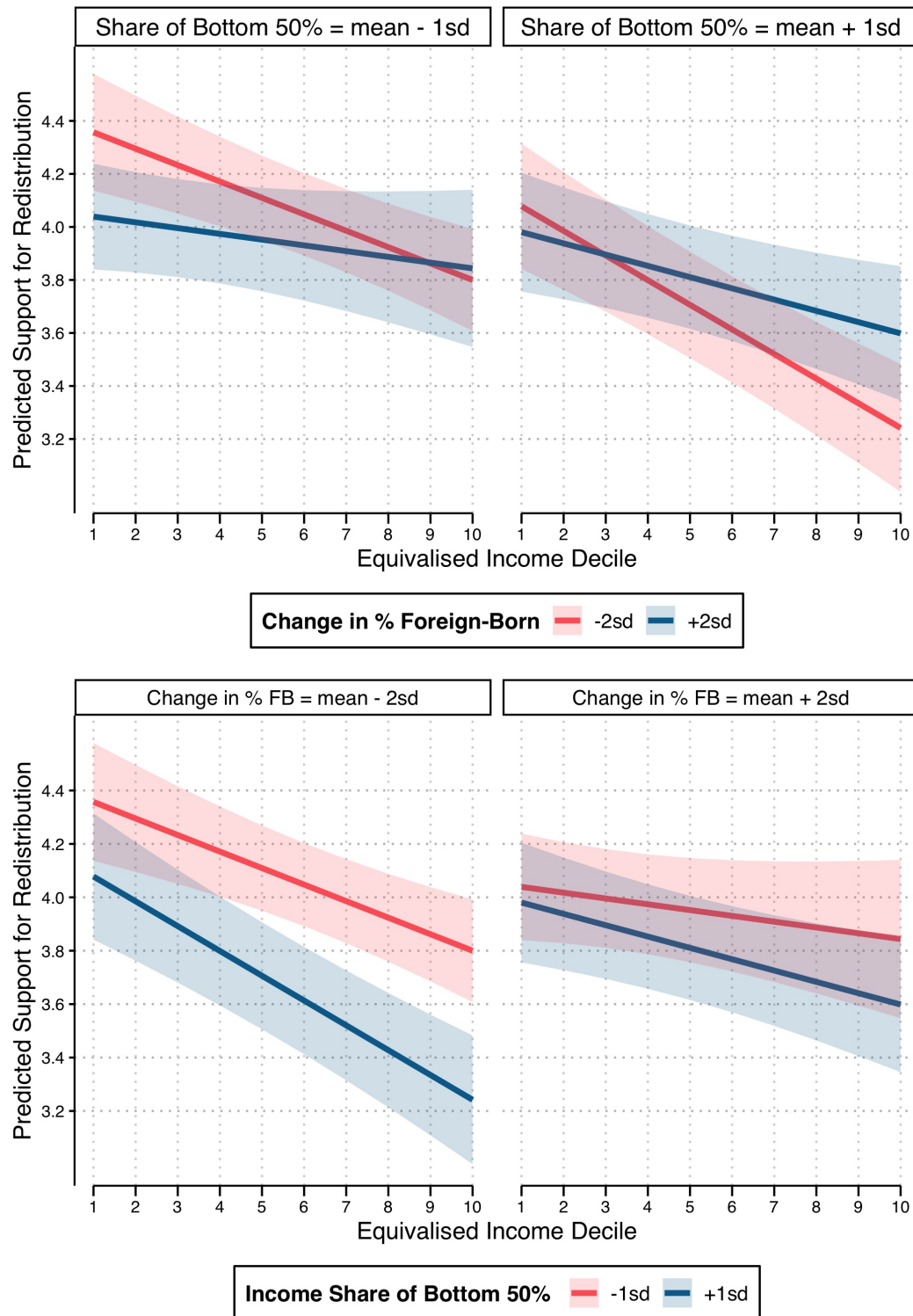


Figure B.21: Predicted Outcomes with Three-Way Interaction - Fixed Effect Model with Clustered SE

C Experimental Evidence

YouGov

To reduce income differences between the rich and poor, the government can raise taxes on all people in the UK to then redistribute income more equally among everyone. Please indicate below how supportive you are of such measures.

Not at all supportive 0 1 2 3 4 5 6 7 8 9 10 Very supportive
□ Don't know

>

(a)

YouGov

Imagine everyone was taxed at the **same rate**. What tax rate would you set?

0% - no tax 100%

□ Not sure

>

(b)

YouGov

Now imagine that there were only two tax rates, one for the **bottom 60%** and one for the **top 40%**

What tax rate would you set for each group?

Bottom 60% of incomes

0% - no tax 100%

□ Not sure

Top 40% of incomes

0% - no tax 100%

□ Not sure

>

(c) T3

Figure C.1: Post-treatment questions

Table C.1: Outcome variable across treatment groups

	median	mean	sd	missing
Continuous Version				
C	6	5.38	2.9	7.9%
T2	5	5.12	3.18	7.5%
T3	5	5.08	2.93	6.5%
T4	5	4.55	3.04	10.4%
Binary Version				
C	0	0.48	0.5	0%
T2	0	0.44	0.5	0%
T3	0	0.46	0.5	0%
T4	0	0.35	0.48	0%

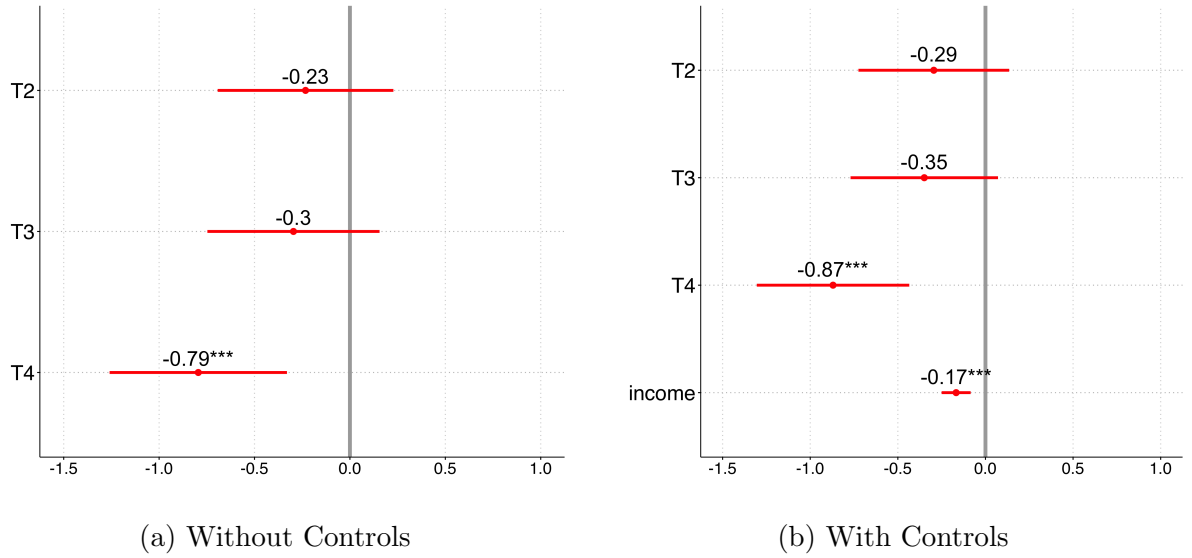


Figure C.2: Estimated (S)ATEs via Regression on Imputed Data

Table C.2: Regression Results (without sampling weights)

		Support for Redistribution			
		Original Data		Combined Imputations	
		(1)	(2)	(3)	(4)
T2		−0.255 (0.237)	−0.286 (0.220)	−0.233 (0.235)	−0.295 (0.219)
T3		−0.299 (0.233)	−0.364* (0.216)	−0.296 (0.23)	−0.349 (0.215)
T4		−0.824*** (0.240)	−0.878*** (0.223)	−0.795*** (0.237)	−0.87*** (0.222)
Income			−0.171*** (0.042)		−0.167*** (0.042)
Female			−0.094 (0.163)		−0.102 (0.162)
Age			0.014** (0.007)		0.014* (0.007)
Tertiary education			−0.041 (0.166)		−0.027 (0.165)
Employment Status Baseline: Not employed	Retired		−0.700** (0.339)		−0.678* (0.338)
	Fulltime		−0.250 (0.251)		−0.253 (0.25)
	Parttime		−0.089 (0.287)		−0.098 (0.287)
Social Grade Baseline: DE	AB		−0.208 (0.267)		−0.195 (0.265)
	C1		−0.541** (0.241)		−0.534* (0.24)
	C2		−0.877*** (0.259)		−0.862*** (0.258)
Political Ideology Baseline: Don't know	Left		1.796*** (0.228)		1.767*** (0.228)
	Centre		0.262 (0.256)		0.23 (0.255)
	Right		−0.869*** (0.244)		−0.884*** (0.244)
Rural			0.095 (0.186)		0.094 (0.185)
Constant		5.377*** (0.170)	5.833*** (0.416)	5.355*** (0.169)	5.808*** (0.414)
Observations		1,326	1,326	1,442	1,442
R ²		0.009	0.163	0.009	0.159
Adjusted R ²		0.007	0.152	0.007	0.149

Note:

*p<0.1; **p<0.05; ***p<0.01

Table C.3: Regression Results (with sampling weights)

		Support for Redistribution			
		Original Data		Combined Imputations	
		(1)	(2)	(3)	(4)
T2		−0.116 (0.240)	−0.149 (0.222)	−0.114 (0.24)	−0.175 (0.224)
T3		−0.185 (0.234)	−0.218 (0.216)	−0.199 (0.233)	−0.223 (0.217)
T4		−0.731*** (0.239)	−0.736*** (0.222)	−0.699** (0.239)	−0.741*** (0.223)
Income			−0.174*** (0.043)		−0.17*** (0.043)
Female			−0.012 (0.163)		−0.029 (0.164)
Age			0.007 (0.007)		0.008 (0.007)
Tertiary education			−0.010 (0.169)		0.009 (0.171)
Employment Status Baseline: Not employed	Retired		−0.571* (0.344)		−0.562 (0.351)
	Full-time		−0.301 (0.253)		−0.296 (0.257)
	Parttime		−0.070 (0.292)		−0.099 (0.299)
Social Grade Baseline: DE	AB		−0.155 (0.272)		−0.15 (0.272)
	C1		−0.501** (0.242)		−0.509* (0.243)
	C2		−0.934*** (0.256)		−0.929*** (0.259)
Political Ideology Baseline: Don't know	Left		1.933*** (0.223)		1.883*** (0.229)
	Centre		0.280 (0.251)		0.241 (0.256)
	Right		−0.772*** (0.239)		−0.808*** (0.243)
Rural			0.065 (0.190)		0.075 (0.192)
Constant		5.249*** (0.169)	5.888*** (0.395)	5.235*** (0.168)	5.878*** (0.396)
Observations		1,326	1,326	1,442	1,442
R ²		0.008	0.166	0.008	0.161
Adjusted R ²		0.006	0.155	0.006	0.151

Note:

*p<0.1; **p<0.05; ***p<0.01

Table C.4: Matches on T4 with full data with sampling weights

Ratio	Replacement	Distance	N° obs	Bias	ATT
1	Yes	propensity score	562	0.055	−0.66*
1	No	propensity score	636	0.045	−0.64*
2	Yes	propensity score	742	0.032	−0.58*
2	No	propensity score	954	0.027	−0.73***
1	Yes	euclidean	580	0.072	−0.66*
1	No	euclidean	636	0.066	−0.5*
2	Yes	euclidean	769	0.073	−0.74**
2	No	euclidean	954	0.057	−0.87***
1	Yes	mahalanobis	554	0.026	−0.69*
1	No	mahalanobis	636	0.031	−0.49*
2	Yes	mahalanobis	730	0.029	−0.65**
2	No	mahalanobis	954	0.037	−0.67**
1	Yes	genetic	568	0.025	−0.67*
1	No	genetic	636	0.026	−0.66**
2	Yes	genetic	741	0.026	−0.44 ⁺
2	No	genetic	946	0.024	−0.57**

Note:

⁺p<0.1; *p<0.5; **p<0.01; ***p<0.001

Table C.5: Matches on T4 with subsetted data (C & T4)

Ratio	Replacement	Distance	N° obs	Bias	ATT
1	Yes	propensity score	486	0.053	−0.98**
1	No	propensity score	626	0.081	−0.8***
2	Yes	propensity score	561	0.036	−0.86**
2	No	propensity score	626	0.081	−0.8***
1	Yes	euclidean	509	0.082	−1.01***
1	No	euclidean	626	0.063	−0.79***
2	Yes	euclidean	584	0.075	−1.03***
2	No	euclidean	626	0.063	−0.79***
1	Yes	mahalanobis	486	0.032	−0.82**
1	No	mahalanobis	626	0.063	−0.79***
2	Yes	mahalanobis	565	0.034	−0.8**
2	No	mahalanobis	626	0.063	−0.79***
1	Yes	genetic	475	0.007	−0.81**
1	No	genetic	626	0.063	−0.79***
2	Yes	genetic	551	0.012	−0.87**
2	No	genetic	468	0.149	−0.17

Note:

⁺p<0.1; *p<0.5; **p<0.01; ***p<0.001

Table C.6: Matches on T2 and T3 with subsetted data

(a) C & T2

Ratio	Replacement	Distance	N° obs	Bias	ATT
1	Yes	propensity score	504	0.046	−0.18
1	No	propensity score	626	0.079	−0.22
2	Yes	propensity score	583	0.037	−0.16
2	No	propensity score	626	0.079	−0.22
1	Yes	euclidean	525	0.077	−0.46 ⁺
1	No	euclidean	626	0.049	−0.24
2	Yes	euclidean	600	0.073	−0.36
2	No	euclidean	626	0.049	−0.24
1	Yes	mahalanobis	515	0.038	−0.42
1	No	mahalanobis	626	0.049	−0.24
2	Yes	mahalanobis	587	0.048	−0.38
2	No	mahalanobis	626	0.049	−0.24
1	Yes	genetic	516	0.018	−0.51 ⁺
1	No	genetic	626	0.049	−0.24
2	Yes	genetic	586	0.013	−0.61*
2	No	genetic	468	0.132	0.39

(b) C & T3

Ratio	Replacement	Distance	N° obs	Bias	ATT
1	Yes	propensity score	548	0.042	−0.57 ⁺
1	No	propensity score	626	0.090	−0.31
2	Yes	propensity score	612	0.043	−0.48 ⁺
2	No	propensity score	626	0.090	−0.31
1	Yes	euclidean	566	0.067	−0.26
1	No	euclidean	626	0.055	−0.25
2	Yes	euclidean	629	0.058	−0.23
2	No	euclidean	626	0.055	−0.25
1	Yes	mahalanobis	563	0.032	−0.43
1	No	mahalanobis	626	0.055	−0.25
2	Yes	mahalanobis	628	0.034	−0.42 ⁺
2	No	mahalanobis	626	0.055	−0.25
1	Yes	genetic	552	0.011	−0.16
1	No	genetic	626	0.055	−0.25
2	Yes	genetic	623	0.016	−0.47 ⁺
2	No	genetic	468	0.141	0.4

Note:

⁺p<0.1; *p<0.5; **p<0.01; ***p<0.001

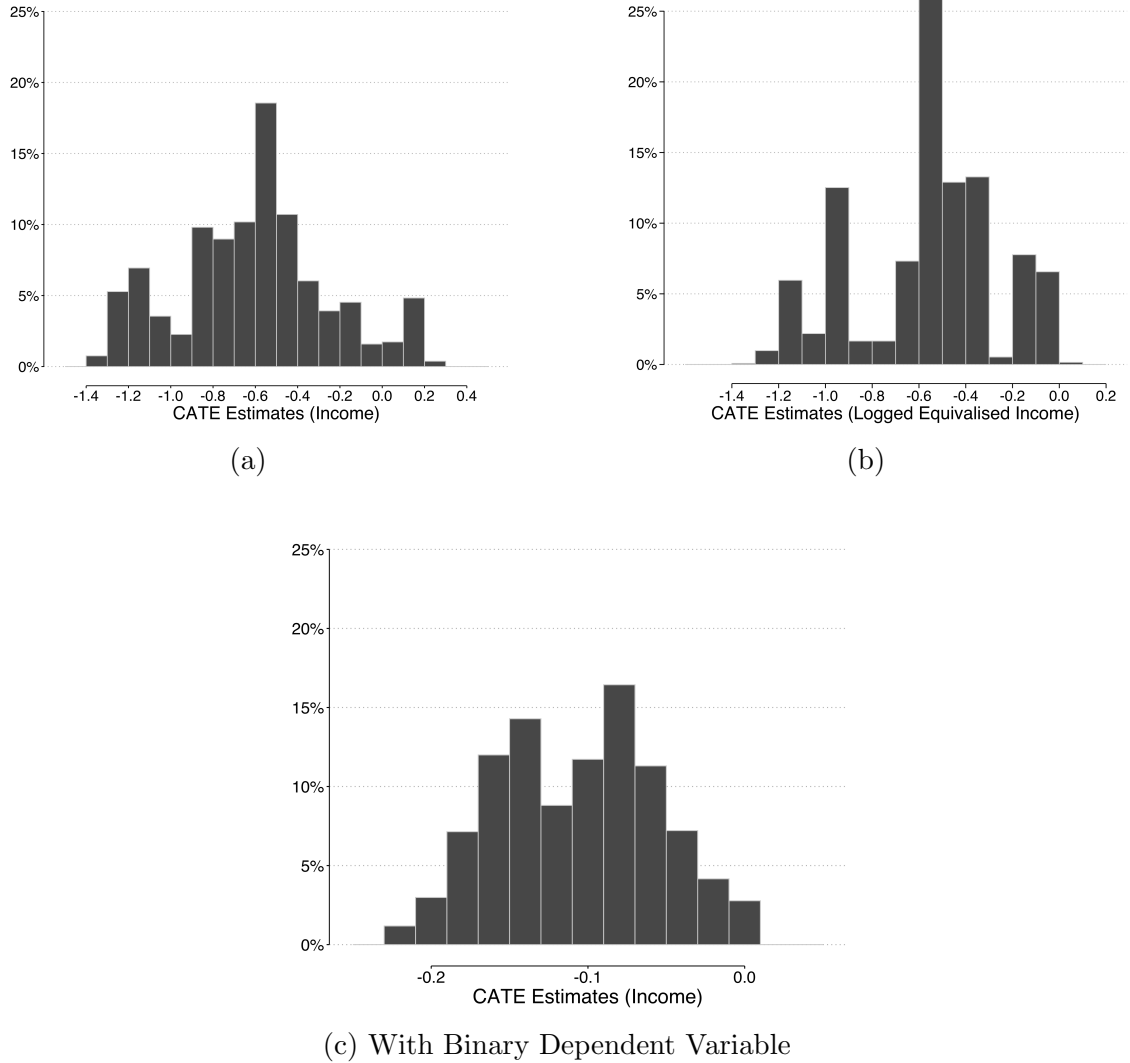


Figure C.3: Out-of-bag CATE from Causal Forests
Shows the distribution of CATE estimates on the training data. These are ‘out-of-bag’ since, for each observation, only the trees that did not use this observation during training are used to calculate the prediction (Tibshirani et al., 2021, “The GRF Algorithm”). These visualisations provides a rough impression of the estimated variability across income in the treatment effect of T_4 relative to no treatment, T_2 and T_3 .

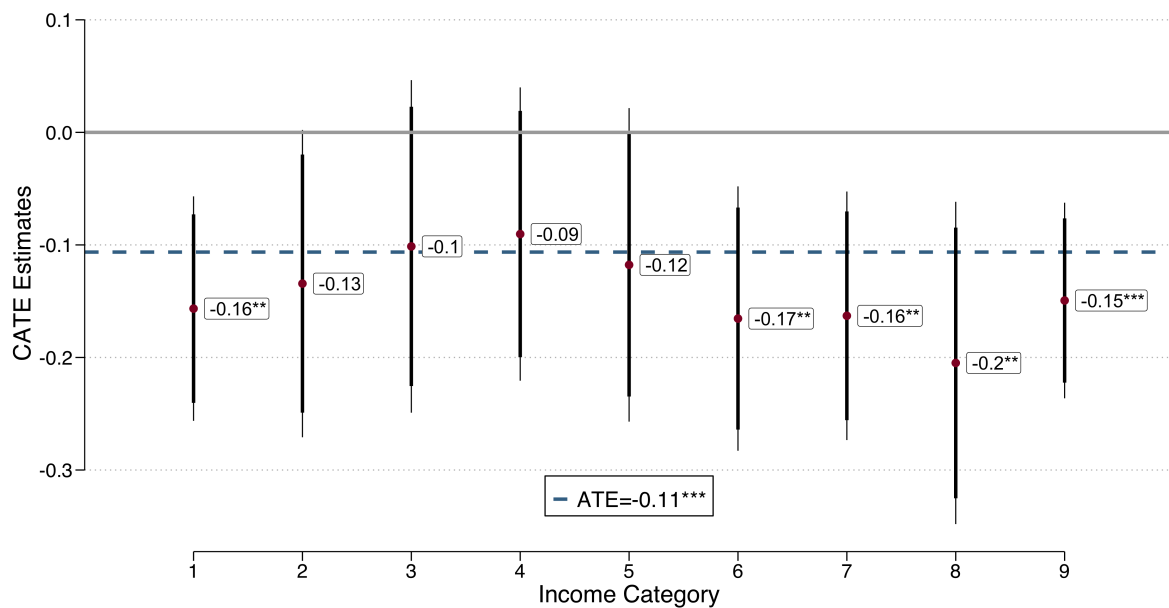


Figure C.4: CATEs estimated via CF with Binary Dependent Variable

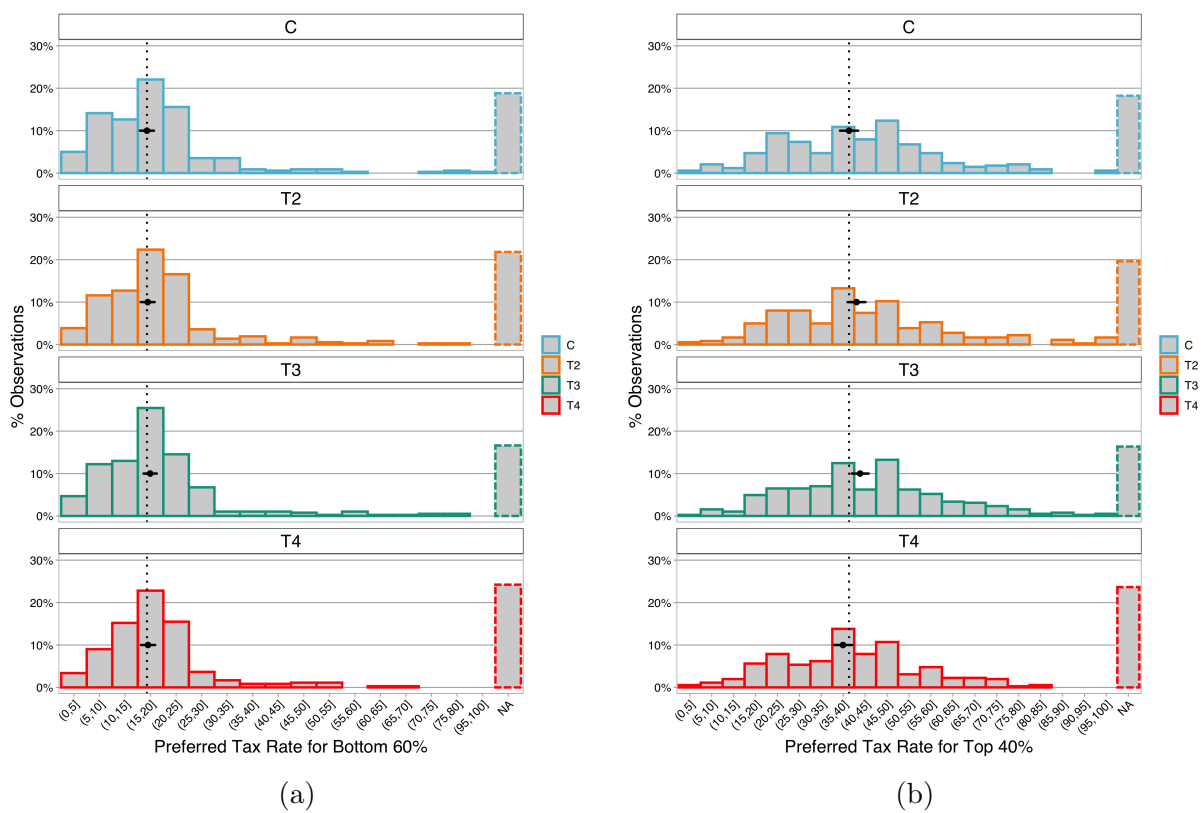


Figure C.5: Preferred tax rates for different income groups by treatment group