Equality or Crime?

Redistribution Preferences and the

Externalities of Inequality in Western Europe

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Abstract

Why is the difference in redistribution preferences between the rich and the poor high in some countries and low in others? In this paper we argue that it has a lot to do with the preferences of the rich and very little to do with the preferences of the poor. We contend that while there is a general relative income effect on redistribution preferences, the preferences of the rich are highly dependent on the macro-level of inequality. The reason for this effect is not related to pocketbook considerations but to a negative externality of inequality: crime. We will show that the rich in more unequal regions in Western Europe are more supportive of redistribution than the rich in more equal regions because of their concern with crime. In making these distinctions between the poor and the rich, the arguments in this paper challenge some influential approaches to the politics of inequality.

Word count: 7627

1 Introduction

The relationship between income inequality and redistribution preferences is a hotly contested topic in the literature on the comparative political economy of industrialized democracies. While some authors maintain that the poor have higher redistribution preferences than the rich (Finseraas 2009; Shayo 2009; Page and Jacobs 2009), others argue that there may not be a negative association between income and redistribution (Moene and Wallerstein 2001; Iversen and Soskice 2009; Alesina and Glaeser 2004: 57-60).

If we were to look at the preferences of rich and poor in different Western European regions, as we do below, we would observe very significant differences in how apart the rich are from the poor regarding their favored levels of redistribution. These important differences in support for redistribution have received little attention in the existing scholarship and yet they are a most significant element in explanations of outcomes as diverse (and as important) as the generosity of the welfare state, political polarization, varieties of capitalism, etc.

In this paper we want to make four related points. First, we argue that material self-interest is an important determinant of redistribution preferences. We show that relative income effects – how far the poor or the rich are from the mean income – explain a significant part of an individual's support for redistribution. Second, and more importantly, we also show that, once pocketbook motivations are accounted for, there is still a great degree of variation in redistribution preferences. We argue that this variation has to do with the preferences of the rich (and not those of the poor) and that they can be explained by taking into account the negative externalities of inequality, namely the relationship between macro-inequality and crime. Third, using data from the European Social Survey, we present a set of empirical tests that support our hypotheses (and provide limited evidence in favor of alternative explanations).

The arguments in this paper challenge some influential approaches to the politics of inequality. These range from those contending that second-dimension issues (particularly cultural and social ones) outweigh economic ones to those emphasizing insurance concerns, social affinity or prospects of upward mobility. We will elaborate on our differences from these approaches in the pages that follow.

2 The Argument

This paper's theoretical argument makes three distinct points about the formation of preferences for redistribution. The first one relates to the idea that the level of redistribution preferred by a given individual is fundamentally a function of current income. The second point distinguishes between income/consumption and non-pocketbook motivations and maintains that non-pocketbook motivations are a luxury good that matters most to those who can afford it, the rich. We will argue that, if we accept that the influence of current pocketbook considerations is sufficiently captured by the micro-effect of relative income, macro-levels of inequality will matter to the rich – and only to the rich – because of non-pocketbook reasons (defined through the paper simply as motivations unrelated to current income, tax and transfers). Our third point proposes that the macro-effect of inequality can be explained by different micro-factors and contends that the most important of these is concern for crime, as a most visible negative externality of inequality.

2.1 Pocketbook considerations

Most political economy arguments start from the assumption that an individual's position in the income distribution determines her preferences for redistribution. The most popular version of this approach is the theoretical model proposed by Romer (1975) and developed by Meltzer and Richard (1981). To recapitulate very briefly, the RMR model assumes that the preferences of the median voter determine government policy and that the median voter seeks to maximize current income. If there are no deadweight costs to redistribution, all voters with incomes below the mean maximize their utility by imposing a 100% tax rate. Conversely, all voters with incomes above the mean prefer a tax rate of zero.

When there are distortionary costs to taxation, the RMR model implies that, by increasing the distance between the median and the mean incomes, more inequality should be associated with more redistribution. The consensus in the comparative literature on this topic, however, seems to be that there is either no association between market income inequality and redistribution or, contrary to the prediction of the RMR model, less market inequality is associated with more redistribution (Lindert 1996; Moene and Wallerstein 2001; Iversen and Soskice 2009; Alesina and Glaeser 2004; Gouveia and Masia 1998; Rodrigiuez 1999: 57-60).

These findings must be considered with a degree of caution. This is because most of this literature relies on macro-comparative empirical analyses (with redistribution as the dependent variable) and does not pay much attention to individual preferences.[1] When looking at individual data, in fact, there is some support for the argument that relative income influences preferences. Using comparative data, a relative income effect is found in, among others, Bean and Papadakis (1998), Finseraas (2009), and Shayo (2009). Using American data, Gilens (2005), McCarty, Poole, and Rosenthal (2008), and Page and Jacobs (2009) (again, among others) find similar effects.

It is important to point out that we go beyond the standard RMR framework by positing that income should affect preferences for redistribution across the entire income distribution. We expect that an individual in, say, the 10th percentile of the income distribution benefits more from the RMR redistributive scheme (lump-sum payments financed by a linear income tax) than an individual in the 30th percentile. As

[1] Even the macro-comparative conclusion is less unambiguous that the consensus in the literature suggests. Milanovic (2000) and Kenworthy and Pontusson (2005) show that rising inequality tends to be consistently associated with more redistribution within countries.

a result, we expect the former individual to have stronger preferences for redistribution than the latter.[2] Note, that in this paper we follow most of the current literature and define redistribution as taxes and transfers and income as present-day income.[3]

2.2 Non-pocketbook motivations as luxury good

The possibility that non-pocketbook motivations may influence redistribution preferences has received increasing amounts of attention in the recent political economy literature. In this paper we define non-pocketbook motivations simply as not related to income, tax and transfer considerations. As we will document below, support for redistribution is widespread in Western Europe and extends into income groups whose support for redistribution could not possibly be motivated by short-term income maximization alone. We will also show that while support of redistribution by the poor is quite constant, support by the rich is shaped by different macro-levels of inequality.

While a most significant approach to non-economic motivations has focused on

[2] The converse holds for the upper end of the income distribution as well. At any given tax rate, someone in the 90th percentile will lose more income than someone in the 70th percentile under the RMR scheme. While, arguably, both individuals may like the tax rate to be zero, the intensity of this preference will vary between the two individuals.

[3] In other words we exclude arguments based on intertemporal perspectives. In the words of Alesina and Giuliano, "(e)conomists traditionally assume that individuals have preferences defined over their lifetime consumption (income) and maximize their utility under a set of constraints" (2011: 93). Because of the potential to define economic material self-interest inter-temporally (as lifetime consumption/income), this approach opens the door to arguments about social insurance and risk (Moene and Wallerstein 2003; Rehm 2009; Iversen and Soskice 2001; Mares 2003) and about social mobility and life-cycle profiles (Alesina and Giuliano 2011; Benabou and Ok 2001; Haider and Solon 2006). We will explore some of the implications of defining economic self-interest inter-temporally in the empirical analysis below (as robustness checks for our findings), but our theoretical starting point is that pocketbook considerations are captured by relative income (the difference between an individual's present income and the mean in her country) and that concern for crime is not related to present income/consumption.

other-regarding concerns (for reviews, see Fehr and Schmidt 2006; DellaVigna 2009), in this paper we will emphasize the importance of the negative externalities associated with inequality. In the section below, we will explain in more detail the reasons why crime is a significant externality of inequality but we start now by clarifying the relationship between pocketbook and non-pocketbook considerations.

As in the Meltzer-Richard model, our argument implies that a rise in inequality that increases the distance between an individual's income and the mean will change her distribution preferences. More importantly, our argument also implies that the pocketbook consequences of inequality are fully contained in the individual income distance changes produced by this inequality rise. In other words, the tax and transfer consequences of inequality are picked up by the individual income changes.

Macro levels of inequality, however, can indirectly affect the individual utility function implicit in the previous paragraph. Following Alesina and Giuliano (2011), we can think about this utility function as one in which individuals care not only about their income/consumption but also about some macro measure of income distribution. In this alternative model, an individual's utility is affected by pocketbook factors (income, taxes and transfers) as well as macro levels of inequality.[4] Of consequence to this paper's argument, this model allows for even the rich to be negatively affected by inequality and, therefore, for them to support redistribution for purely self-interested reasons.

We are not the first authors to recognize the externalities of inequality as a specific case of a more general model of support for redistribution with macro-inequality concerns as well as individual pocketbook considerations.[5] Perhaps the clearest

[4] As suggester by Alesina and Giuliano (2011), different individuals may be affected by different kinds of inequality. For simplicity, in this paper we focus on the Gini coefficient, which is the most commonly used measure of inequality in the political economy literature.

[5] The literature in economics and political economy has identified a number of other externalities. If we assume the poor to be less educated, a less effective democracy has been considered a negative

example is the literature on externalities of education, which connects average levels of education with aggregate levels of productivity (see, for example, Nelson and Phelps (1966), Romer (1990) and Perotti (1996)). This framework proposes that, with imperfect credit markets, more inequality means more people below an income level that would allow them to acquire education. The rich, in this case, would support redistribution because of the benefits of a higher education average. But, to our knowledge, we are the first to emphasize crime as the key explanatory factor behind the affluent's support for redistribution.[6]

The paragraphs above suggest that both pocketbook and non-pocketbook considerations about the negative externalities of inequality matter to redistribution preferences. To integrate the arguments about these two distinct dimensions, however, we will argue that a hierarchy of preferences exists. We propose that poor people value redistribution for its immediate pocketbook consequences. The redistributive preferences of the rich, on the other hand, are less significantly affected by pocketbook considerations. For the rich, the negative externalities of inequality can become more relevant.

We conceive of the solution to the negative externalities of inequality as a luxury good that will be more likely to be consumed when the need for other basic goods has been satisfied. The idea that less immediate concerns can be trumped by more immediate pocketbook ones for the poor is compatible with previous political economy work on material and non-material incentives. Levitt and List construct a model in

externality of inequality by authors like Milton Friedman (1982). There is also some research connecting inequality and environmental degradation (Boyce 1994). And see Beramendi (2012) for an analysis of the externalities of regional inequality.

[6] While not focusing on the redistribution preferences of the affluent, there is a considerable literature in economics and sociology suggesting that there is a link between crime and inequality (e.g. Ehrlich 1973; Freeman 1983; Fowles and Merva 1996; Kelly 2000; Fajnzlber, Lederman, and Loayza 2002; Choe 2008)

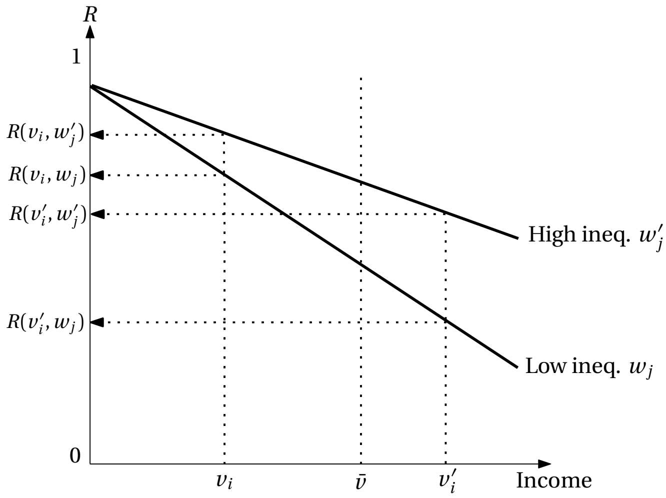

Figure 1: Macro-Inequality and Support for Redistribution

which individuals maximize their material gains but, when wealth-maximizing action has a non-economic cost, they deviate from that action to one with a lower cost (2007: 157). More importantly, they also argue that, as the stakes of the game rise, economic concerns will increase in importance relative to non-economic ones. We argue in this paper that higher stakes (i.e., the poor's need for the benefits of redistribution) increase the importance of pocketbook considerations as a determinant of redistribution preferences. Lower stakes for the rich (there are costs to increasing redistribution, but for the rich they do not involve dramatic consequence comparable to those for the poor) mean that the negative externalities of inequality will be more important.

The implications of this paper's argument are summarized in Figure 1. We expect the negative externalities of inequality to be associated with less support for redistribution. Since we argue that for the poor non-economic concerns are trumped by material incentives, redistribution preferences converge regardless of the macro-level of inequality as income declines. Thus, the redistribution preferences of an individual with low income v_i in a low inequality region w_j, denoted $R(v_i, w_j)$, and in a high inequality region $R(v_i, w'_j)$ do not differ by much. In contrast, we expect more macro-inequality to promote concerns for its negative externalities only for the rich, so that redistribution preferences of a rich individual in a low income region $R(v_i', w_j)$ differ starkly from those in high inequality regions $R(v_i', w_j')$.

2.3 Macro-inequality and fear of crime

We will show below that the association between macro-inequality and redistribution preferences summarized in Figure 1 is supported by the empirical evidence and extraordinarily robust. We argue that the effect of macro-inequality is channeled by a number of different micro-factors. The most important of this, as mentioned above, is crime, as a most visible negative externality of inequality.

The canonical model for the political economy of crime and inequality was originally developed by Becker (1968) and first explored empirically by Ehrlich (1973). The basic argument is simple (see a nice explanation in Bourguignon 1999). Assume that society is divided into three classes (the poor, the middle and the rich) with increasing levels of wealth. Assume further that crime pays a benefit, that there is a probability that crime will result in sanction/punishment and that the proportion of "honest" individuals (people who would not consider crime as an option regardless of its economic benefits) is independent of the level of income (and distributed uniformly across classes). It follows from this straightforward framework that rich people for whom the benefit of crime is small in proportion to their initial wealth will very rarely find crime attractive. It also follows that there will always be a proportion of people among the poor who will engage in crime, and that the benefits from crime are proportional to the wealth of the population. The crime rate implied by this simple model would be positively correlated to the extent of poverty and inequality and negatively correlated to the probability of being caught, the cost of the sanction/punishment, and the proportion of "honest" individuals.

Following this framework, the intuition that crime is related to inequality is easy to understand. With more inequality, the potential gain for the poor from engaging in crime is higher and the opportunity cost is lower. Some early empirical analyses supported this intuition (Ehrlich 1973; Freeman 1983),[7] but the evidence is not unambiguous. However, while we have described above the relationship between inequality and objective levels of crime, it is fear of crime by the affluent that matters most to our argument. We do understand that, as shown by a well-established sociology literature, fear of crime does not exactly reflect the objective possibility of victimization. As early as 1979, DuBow, McCabe, and Kaplan showed that crime rates reflect victimization of the poor (more than the rich) and that fear levels for particular age-sex groups are inversely related to their victimization (elderly women having the lowest victimization rates but the highest fear of crime, young men having the opposite combination).[8] While we do model explicitly the determinants of fear of crime in the empirical analysis we develop below (and show that macro-inequality is a significant one), we are not interested in them per se. Our argument simply requires rich individuals to perceive regional crime rates and to believe that there is a connection between macro-inequality and crime (following the intuitive logic of the Becker model summarized above). This connection makes sense even if the affluent have concerns for crime that are disproportionately high given their objective probability of victimization.

[7] More recently, Fajnzlber, Lederman, and Loayza (2002) use panel data for more than 37 industrialized and non-industrialized countries from the early 1970s until the mid-1990s to explore the relationship between inequality and violent crime. They find crime rates and inequality to be positively correlated within countries and, particularly, between countries.

[8] On the other hand, the effect of victimization on fear of crime may not be a direct one exactly reflecting the objective possibility of being a victim. The indirect victimization model in sociology proposes that fear of crime "is more widespread than victimization because those not directly victimized are indirectly victimized when they hear of such experiences from others, resulting in elevated fear levels" (Covington and Taylor 1991: 232).

To anticipate some of our empirical choices below, two additional observations are needed about our argument that macro-inequality reflects individual concerns about crime as a negative externality. The first one is about the level of macro-inequality. Our theoretical argument proposes that the importance of inequality emerges from its relationship to crime as a negative externality. This implies that the relevant level of macro-inequality should be one at which a visible connection to crime could be made by individuals. We therefore move away from national data and use regional levels of inequality in the analysis below. We argue that, unlike more aggregate levels, regional inequality is visible and that it is plausible to assume that it would be related to fear of crime by rich individuals. While it would be good to use even more disaggregated units (like neighborhoods, as in some crime research) the availability of the data at our disposal limits what we can do.

Our argument also implies that it is reasonable to expect rich individuals, who are more concerned about crime because they live in more unequal areas, to be more likely to support redistribution. We assume the affluent's concern for crime to be causally connected to macro-inequality, and higher redistribution to be perceived as one of the solutions to the problem. It is clear that other solutions are possible. Most importantly, the affluent may demand protection as a solution to crime (rather than redistribution as a solution to its cause). Recall that objective crime rates in Becker's model is negatively correlated to the probability of being caught and the cost of the sanction/punishment. As argued by Alesina and Giuliano (2011), the implicit assumption in the kind of argument made in this paper is that it should costs less to the rich to redistribute than to increase spending on security. While we recognize this as an important issue, we do not consider demands for protection to be incompatible with preferences for redistribution. In Western Europe, where the empirical analysis below focuses on, it is reasonable to expect the rich to think of redistribution and protection as complementary policies to mitigate regional crime.[9]

3 Data

To explore the theoretical claims explained above, we will first consider the effects of income distance at the individual level and of the macro-level of inequality. Income distance is meant to capture the effects of individual pocketbook considerations and macro-inequality those of non-pocketbook factors. The first expectation is that income distance will be a significant determinant of redistribution preferences. We also expect, however, that increasing levels of regional inequality will make the rich more likely to support redistribution. We will then show that the very robust effects of macro-inequality are in fact the product of fear of crime among the affluent.

Source and coverage of survey data We use data from the European Social Survey, which includes consistent regional level identifiers allowing us to match individual and regional information while working with usable sample sizes.[10] It also provides a consistent high quality measure of income. We limit our analyses to surveys collected between September 2002 and January 2009, which was still a time of relative economic calm.[11] Our data set covers 129 regions in 14 countries: Austria, Belgium, Germany, Denmark, Spain, Finland, France, Great Britain, Ireland, Netherlands, Norway, Portugal, Sweden, and Switzerland surveyed between 2002 and early 2009.

[9] It is also reasonable to expect the level of privately financed security available in Western Europe to be lower than, for example, in the USA (where gated communities and private protection are more common).

[10] Regional level identifiers are provided by the NUTS system of territorial classification (Eurostat 2007). We selected countries who participated in at least two rounds (to obtain usable regional sample sizes) and which provided consistent regional identifiers over time.

[11] We also eliminate surveys after 2007 as a robustness check. See details below.

Redistribution preferences Our dependent variable, preferences for redistribution, is an item commonly used in individual level research on preferences (e.g., Rehm 2009). It elicits a respondent's support for the statement "the government should take measures to reduce differences in income levels" measured on a 5 point agree-disagree scale. To ease interpretation we reverse this scale for the following analyses.

Western Europe is characterized by a rather high level of popular support for redistribution. While almost 70% of respondents either agree or strongly agree with the statement that the government should take measure to reduce income differences, only 15% explicitly express opposition to redistribution. However, despite this apparent consensus, there exists substantial regional variation in redistribution preferences as well as between rich and poor, as we will show below.

The measure of relative income Our central measure of material self-interest is the distance between the income of respondents and the mean income in their country (at the time of the survey). The ESS captures income by asking respondents to place their total net household income into a number of income bands (12 in 2002-06, 10 in 2008) giving yearly, monthly, or weekly figures.[12] To create a measure of income that closely represents our theoretical concept, income distance, we follow the American Politics literature and transform income bands into their midpoints. For example, this means that category band J (Less than Eur 1,800) becomes mid-point Eur 900 and category R (Eur 1,800 to under Eur 3,600) becomes Eur 2,700. We convert the top-coded income category by assuming that the upper tail of the income distribution

[12] It uses the following question: "Using this card, if you add up the income from all sources, which letter describes your household's total net income? If you don't know the exact figure, please give an estimate. Use the part of the card that you know best: weekly, monthly or annual income." Two different cards are shown to respondents, depending on the year of the survey. In the surveys from 2002 to 2006, the card places the respondent's total household income into 12 categories with different ranges. The survey for 2008 offers 10 categories based on deciles in the country's income distribution.

follows a Pareto distribution (e.g., Kopczuk, Saez, and Song 2010, for details see Hout 2004). The purchasing power of a certain amount of income varies across the countries included in our analysis. Simply put, it could be argued that the meaning of being Eur 10,000 below the mean is different in Sweden than in the United Kingdom. Thus, we convert Euros or national currencies into PPP-adjusted 2005 US dollars. Finally, for each respondent we calculate the distance between her household income and the mean income of her country-year survey.

Crime We measure individuals' crime concerns via a survey item that has become "the de facto standard for measuring fear of crime" (Warr 2000: 457). It prompts a respondent if he or she is afraid of walking alone in the dark with 4 category responses ranging from "very safe" to "very unsafe". As we discussed above, this captures crime concerns as externality of inequality, instead of actual crime. We also use a measure of actual crime victimization, see details below, that is based on asking respondents if they or a member of their household have been a victim of burglary or assault within the last five years.

Inequality To measure inequality a wide number of indices are available, of which the Gini index is the most popular one (e.g., Jenkins 1991). We perform a subgroup-decomposition of the Gini into its regional components (on the sub-group decomposability of inequality indices see Shorrocks 1980, 1984; Silber 1989; Cowell 1989).[13] We calculate our regional Gini measure from our full sample of individual level data.

[13] Decomposability means that an index can be decomposed into three group-components: $B+W+k$, where W and B represent within- and between group variance, respectively, while k is a residual component. An index is perfectly decomposable if $k=0$. This is true, for example, for members of the family of Generalized Entropy measures; but it is not necessarily true for the Gini. We decided to use Gini in our main text since it is the most common measure. However, we replicated our results using the Theil index (obtained from a generalized entropy measure with parameter 1), which is perfectly decomposable. The correlation between it and our (small-N corrected) Gini measure is 0.98.

Following current 'best practice' in economics, we correct for non-random sampling and small-sample bias. Sample selection effects are taken into account by using an estimator that weights according to a household's sample inclusion probability (e.g., Cowell 2000). Since, it is well known that Gini estimates are downward biased when calculated from small sample sizes, we employ the correction proposed by Deltas (2003).

At this point we only have the usual point estimate of Gini inequality. However, Gini values are estimated with error, a fact that is often ignored in current research and leads to classical errors-in-variables bias in one's results. To account for measurement error in our Gini estimates we proceed in two steps. First we need an estimator of the variance of our Gini estimates. Second, we need to account for this variance in our statistical model estimated below.

Following Karagiannis and Kovacevic (2000), we use a jacknifing variance estimator to generate regional Gini standard errors.[14] Thus, for each Gini value, we have a point estimate $\hat{w}_j$ and a standard error $\sqrt{\text{Var}(\hat{w}_j)}$. In our analysis model (described below), we correct for measurement error following the methodology outlined by Blackwell, Honaker, and King (2012), who propose to treat measurement error in the framework of missing data. One creates several (about 5) "multiply overimputed" data sets, in which the variable measured with error is drawn from a suitably specified distribution representing the variable's measurement error. To implement this idea, we generate 5 overimputed data sets with Gini values for each data set drawn from

$$w_j \sim N\left(\hat{w}_j, \text{Var}(\hat{w}_j)\right)$$

[14] An alternative strategy is to bootstrap Gini estimates. However, this is computationally a lot more expensive than the jackknife style estimator, and test conducted by us show that generated standard errors are identical at the second digit.

To illustrate the 'penalty' incurred by this measurement error technique, we plot, in Figure 2, three regions with similar Gini estimates, but different standard errors. Région lémanique (in Switzerland), Niedersachsen (in Germany), and Noord-Friesland (in the Netherlands) share an estimated regional Gini between around 0.31 and 0.32. For each region we show the Gini estimate as black dot and five random multiple-overimputation draws as gray diamonds. Figure 2 clearly shows how larger Gini standard errors lead to a considerable increase in the variance of overimputed values. We use these overimputed values to estimate all our models five times; average our estimates and penalize standard errors as a function of the variance between overcompensation as suggested in Blackwell, Honaker, and King (2012) or Rubin (1987). In essence, we account for the errors-in-variables problem caused by the uncertainty of Gini estimates, and we generate conservative standard errors.

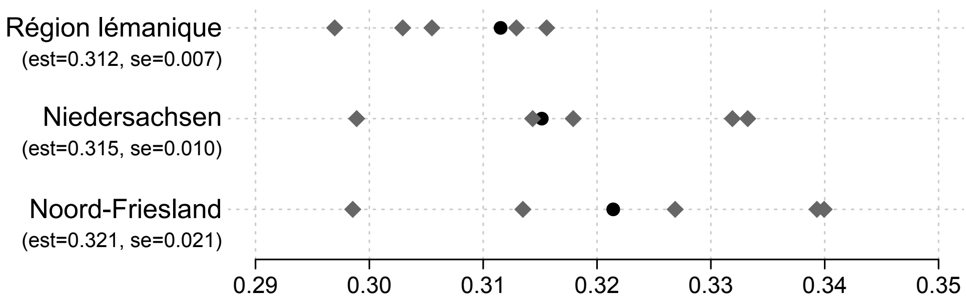

Figure 2: Illustration of multiple overimputation of Gini measurement error

Individual- and regional-level controls We control for a range of standard individual characteristics, namely a respondent's gender, age in years, years of schooling, indicator variables for currently being unemployed, or not in the labor force, and the size of one's household. We include a measure of social class. While social class is theoretically somewhat ambiguous, it allows us to capture a broad range of socio-economic outcomes which might be confounded with our income and inequality measures. Furthermore, we include a measure of specific skills, differentiating between high and low general skills, and specific skills. As controls for existing regional differences we include the harmonized regional unemployment rate, gross-domestic product, the percentage of foreigners (see, e.g., Alesina and Glaeser 2004, Finseraas 2008) and a summary measure of a region's high-tech specialization[15]. Descriptive statistics for all variables can be found in online supplement S.1.

Multiple imputation We use multiple imputation to address missing values. It is well known that listwise deletion or various 'value substitution' methods are likely to produce biased estimates and standard errors that are too small (Allison 2001; King et al. 2001; Little and Rubin 2002). Using multiple imputation we not only obtain complete data sets, but (more importantly) generate conservative standard errors reflecting uncertainty due to missing data (Rubin 1987, 1996). An additional advantage of using multiple imputation is that we can use auxiliary variables that are not used in our analyses to predict missing responses, yielding so called "superefficient" imputations (Rubin 1996). As additional predictors we include a set of variables which help us predict missing income, such as the number of dependent children, living in an urban or rural area, ideology, as well as questions on satisfaction with one's current income, assessment of subjective health, and general life satisfaction. Multiple imputations are created by random draws from a multivariate normal posterior distribution for the missing data conditional on the observed data (King et al. 2001). These draws are used to generate five complete (i.e., imputed) data sets. All our analyses are performed on each of these five data sets and then averaged with standard error adjusted to reflect the uncertainty of the imputed values (Rubin 1987).[16]

[15] We used a factor model to generate a summary measure for regional high-tech specialization. We collected Eurostat data on regional information on the share of a region's total workforce employed in science and technology sectors, the share of the economically active population that hold higher degrees, a head count of personnel employed in R&D, and regional total R&D expenditure.

[16] Note that we have also estimated our results using 'simple' listwise deletion and obtained qualitatively similar results.

4 Methodology

Models In the first stage of our analysis we study the link between inequality, relative income, and redistribution preferences R_i^*. Our model specification is

$$R_i^* = \alpha(v_i - \bar{v}) + \beta w_j + \gamma w_j(v_i - \bar{v}) + \boldsymbol{\delta}'\boldsymbol{x}_{ij} + \epsilon_{iR}. \tag{1}$$

Here α captures the effect of relative income, the difference between an individual's income v_i and country-year average income $\bar{v}$. The remaining (non-pocketbook) effect of macro inequality w_j is captured by β. Since we argue that inequality effects are more relevant among the rich than among the poor, our model includes an interaction between inequality and individual income with associated effect coefficient γ. Finally, we include a wide range of individual and regional level controls $\boldsymbol{x}_{ij}$ whose effects are represented by $\boldsymbol{\delta}$.

Redistribution preferences R_i^* are a latent construct obtained from observed categorical survey responses R (with K_r categories) via a set of thresholds (e.g. McKelvey and Zavoina 1975; Greene and Hensher 2010) such that $R = r$ if $\tau_{r-1} < R^* < \tau_r$ $(r = 1, \ldots, K_r)$.[17] Thresholds $\boldsymbol{\tau}$ are strictly monotonically ordered and the variance of the stochastic disturbances is fixed at $\epsilon_{iR} \sim N(0, 1)$ yielding an ordered probit

[17] This model thus imposes what is known as the single-crossing property, which follows directly from the theoretical assumption of single-peaked preferences: as one moves along the values of x, the predicted probability $Pr(y = r)$ changes only once (Greene and Hensher 2010; Boes and Winkelmann 2006). As Greene and Hensher (2010) argue at length, models that do not enforce this restriction (such as multinomial or generalized ordered logit modes) are not appropriate for strictly ordered preference data. An argument that is sometimes made (especially in the sociology literature) is that one should conduct a Brant test, which compares an ordered specification with an 'unordered' one. However, since an unordered specification is clearly an inappropriate *behavioral* model for the data used here, we do not pursue this further. For further arguments against these kind of test see Greene and Hensher (2010).

specification.[18]

In the second stage of our analysis we jointly model fear of crime and preferences for redistribution. Our fear of crime variable C is also ordered categorical and we use the same ordered probit specification as above, i.e., $C = c$ if $\tau_{c-1} < C^* < \tau_c$ ($c = 1, \ldots, K_c$) with strictly ordered thresholds and errors $\epsilon_{iC} \sim N(0,1)$ for identification. Errors from the redistribution and crime equations are correlated and thus specified as distributed bivariate normal (Greene 2002: 711f.):

$$[\epsilon_{1i}, \epsilon_{1i}] \sim BVN(0,0,1,1,\rho),$$

where ρ captures the residual correlation between both equations.

A direct test for our argument that fear of crime is an important externality shaping redistribution preferences is to estimate its effect in our redistribution equation. We thus arrive at the following simultaneous (recursive) system of equations (Greene and Hensher 2010: ch.10):[19]

$$C_i^* = \alpha_1(v_i - \bar{v}) + \beta_1 w_j + \boldsymbol{\delta}_1' \boldsymbol{x}_{1ij} + \epsilon_{iC} \tag{2}$$

$$R_i^* = \lambda_1 C_i + \lambda_2 C_i(v_i - \bar{v}) + \alpha_2(v_i - \bar{v}) + \beta_2 w_j + \gamma w_j(v_i - \bar{v}) + \boldsymbol{\delta}_2' \boldsymbol{x}_{2ij} + \epsilon_{iR}. \tag{3}$$

Thus this model can be seen as a straightforward extension of the more familiar bivariate probit model to ordered data (Butler and Chatterjee 1997).[20] In order not

[18] An ordered probit model needs two identifying restrictions. Besides setting the scale by fixing the error variance, we fix the location by not including a constant term (but estimate all thresholds).

[19] The system is recursive because C_i is allowed to influence R_i but not vice versa. The model employs the standard assumption that $E(\epsilon_{iC}|\boldsymbol{x}_{1ij}, \boldsymbol{x}_{2ij}) = E(\epsilon_{iR}|\boldsymbol{x}_{1ij}, \boldsymbol{x}_{2ij}) = 0$.

[20] See Yatchew and Griliches (1985) for a discussion of the disadvantages of two-step estimation. Freedman and Sekhon (2010) caution against convergence to local maxima, which we check by (i) running our model several times from dispersed initial values, (ii) bootstrapping individual observations. In each case we get essentially the same results.

to rely on function form alone for identification, $\boldsymbol{x}_{1ij}$ should contain at least one covariate excluded from the redistribution equation. The literature on determinants of fear of crime includes a number of 'standard' variables related to the probability of victimization, such as social class, education, age, and gender. However these variables are all relevant controls in our redistribution equation as well. Thus we use actual victimization, that is if the respondent reports that he, or a member of his household, has been a victim of crime, which is plausibly excluded from the redistribution equation.

Estimation We estimate these two equations jointly by maximum likelihood (Butler and Chatterjee 1997). In this setup, individuals within the same region and country will share unobserved characteristics, rendering the standard assumption of independent errors implausible (e.g., Moulton 1990; Pepper 2002). Thus, to account for arbitrary within region and country error correlations we estimate standard errors using a nonparametric bootstrap resampling regions and countries.[21]

In this second stage, our main interest lies on λ_1 and λ_2 which capture the effect of fear of crime (and its interaction with income) on redistribution preferences net of all other covariate effects. Our model still includes the main effect of income distance α_2 as well as the remaining effect of inequality β_2 and its interaction with income distance, captured by γ. Estimates of individual and regional level controls $\boldsymbol{x}_{ij}$ are given by $\boldsymbol{\delta}$.

Ideally, if fear of crime plays a significant role in explaining redistribution prefer-

[21] There are two possible alternative strategies, 'cluster-robust' standards errors and explicit 'multilevel models'. Robust standard errors should be specified on the highest level of clustering, which in our case would imply 14 clusters. Angrist and Pischke (2008) discuss the possibly large bias that can arise with robust standard errors for few clusters. Similar objections have been raised against using multilevel models for small-sample country data. Stegmueller (2013) presents clear evidence that standard errors are likely to be *too small*. Thus we opt for the nonparametric bootstrap as a computationally expensive, but more conservative, alternative (e.g., Wooldridge 2003).

ences, we expect to see at least (i) a significant effect of inequality on fear of crime: $\beta_1 \neq 0$, (ii) a significant effect of fear on preferences: $\lambda_1 \neq 0$ and a reduction of the (remaining) effect of inequality on the rich γ vis-a-vis equation (1).

5 Regional variation in inequality and preferences

We have argued above that rich individuals who are more concerned about crime because they live in more unequal areas will be more likely to support redistribution. Figure 3 represents a first illustration of the two things this paper's argument is about: the existence of regional variation in support for redistribution among the rich and the poor. Figure 3 captures the average level of support (i.e., the mean of the 5-point scale) for redistribution in each of the regions in the sample. First among the rich (those with household incomes 30,000 PPP-adjusted 2005 US dollars above the mean, the 90th percentile in the sample's income distribution) and then among the poor (with household incomes 25,000 PPP-adjusted 2005 US dollars below the country-year mean, the 10th percentile).

Figure 3 strongly suggest the existence of a general relative-income effect. By looking at the two panels side by side, we can see that the support for redistribution of the poor is almost always higher than that of the rich (there are some exceptions, but these are limited to very few regions where support for redistribution is generally very high for both groups). While the poor's average regional support for redistribution is close to 4 in the 5-point scale (the "Agree" choice), the average for the rich is closer to 3 (the "Neither agree nor Disagree" choice). Figure 3 also shows a remarkable amount of regional variation. The lowest support for redistribution among the rich (2.2 on the 5-point scale, close to the "Disagree" choice) can be found in a Danish region (Vestsjællands amt), while the highest support among the rich (4.6) is in a Spanish one (La Rioja). For the poor, the highest support for redistribution (4.5) is in France (Champagne-Ardenne, Picardie and Bourgogne) while the lowest support

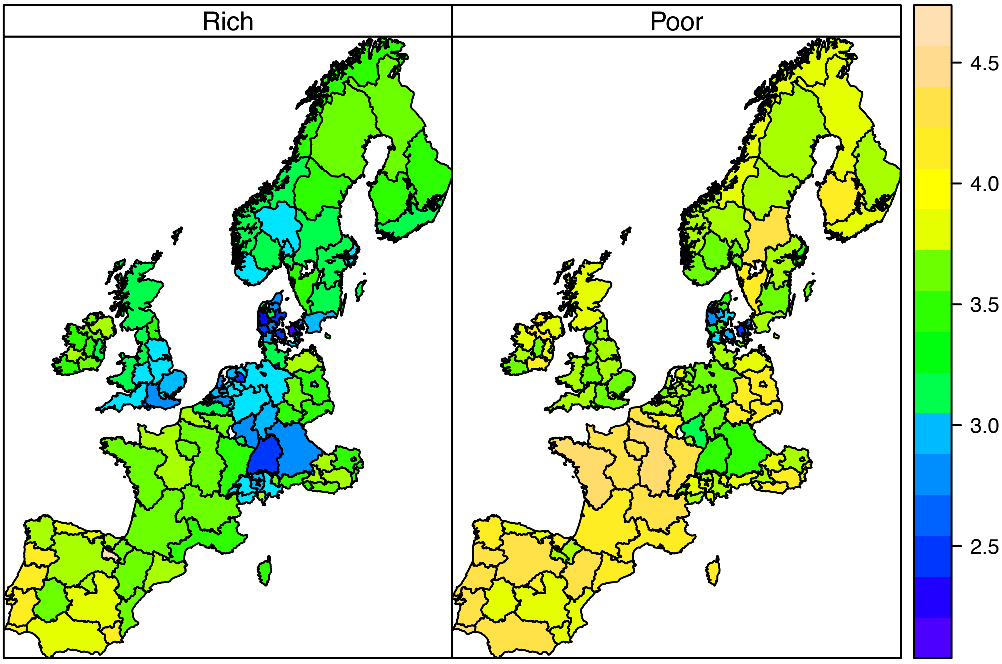

Figure 3: Average regional redistribution preferences among Rich and Poor

(2.6) is again to be found in Vestsjællands Amt.

More importantly for the arguments in this paper, the degree of regional variation within countries in Figure 3 is remarkable. Looking at the redistribution preferences of the rich, this variation can be illustrated by comparing two regions in the United Kingdom. In the South East of England, the rich exhibit a low support for redistribution (2.8) while in Northern Ireland they are much more supportive (3.8, a whole point higher). The preferences of the poor can also be used as an illustration. In Denmark, the poor in Storstrøms Amt are much more supportive of redistribution (3.7) than in Vestsjællands Amt (2.6).

Figure 4 reflects more directly the regional differences between the rich and the poor. Figure 3 suggested that support for redistribution was generally high in regions in Spain, France, Ireland and Portugal and low in regions in Denmark, Germany, Great Britain, Belgium and the Netherlands. The support of redistribution among the rich and the poor mirrors these general trends, but the differences between poor and rich are interesting. For example, in some regions in France, Sweden and Norway, where

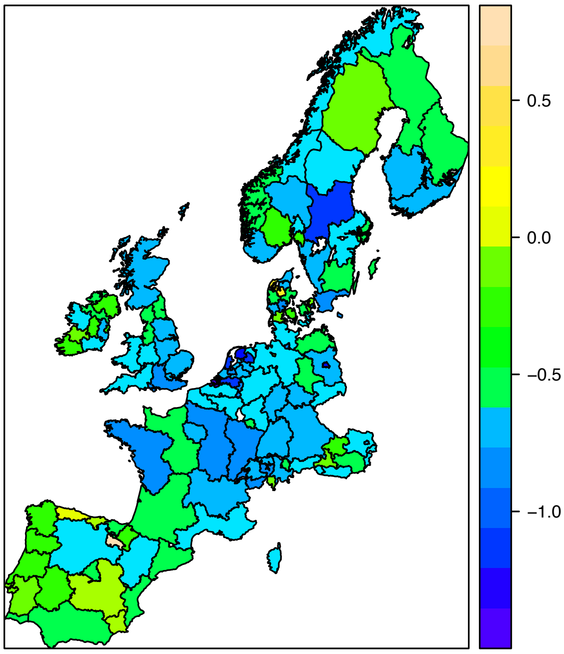

Figure 4: Regional differences in redistribution preferences between Rich and Poor

the general support for redistribution is relatively high, the difference between rich and poor is large (around 1, of the 5-point scale). In some regions in Spain and Portugal, where the general support for redistribution is again relatively high, the difference between rich and poor is low (below 0.5). There are regions with low general levels of support for redistribution that have small differences between the rich and poor in Denmark (Viborg Amt and Frederiksborg Amt) or Austria (Salzburg). And there are regions with similarly low general levels of support that have big differences between the rich and poor in the Netherlands (Friesland, Noord-Holland and Zeeland) or Germany (Berlin and Hamburg).

The more systematic analysis to be developed below will help explain the redistribution patterns shown in Figures 3 and 4, but an initial illustration of our main explanatory variables is offered in Figures 5 and 6. Figure 5 captures regional inequality (the Gini index calculated from the individual-level surveys as explained in previous sections) and Figure 6 fear of crime (measured as the regional average of the 4-category responses to the survey question about respondents being afraid of walking

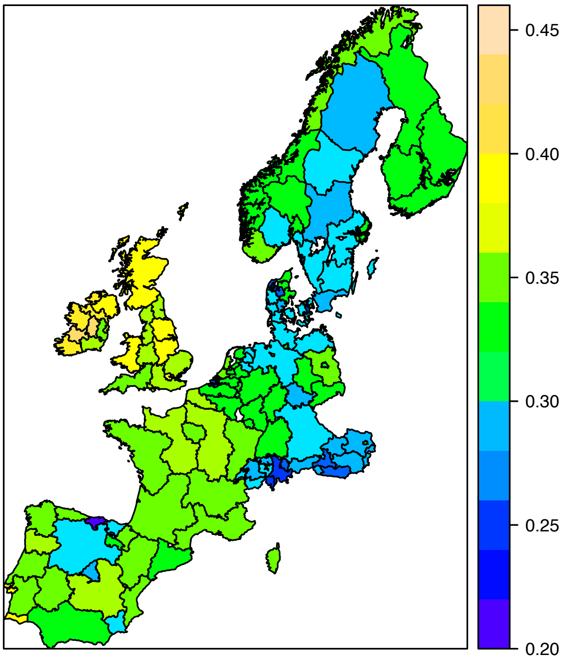

Figure 5: Inequality by region

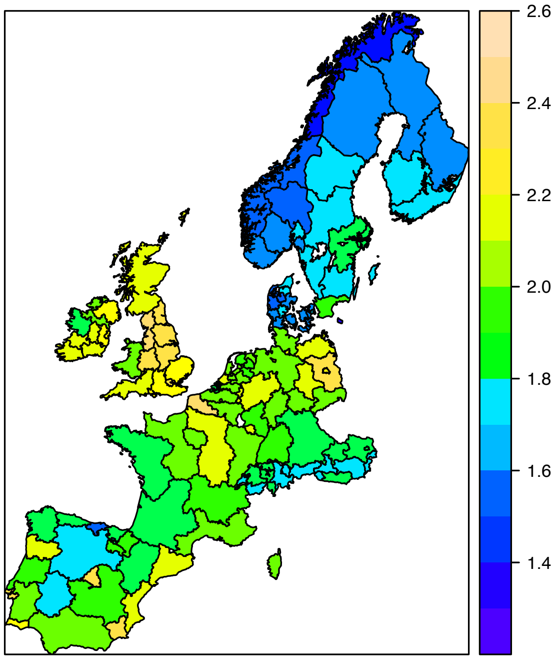

Figure 6: Fear of crime by region

alone in the dark). The figures again show a remarkable amount of regional variation and, while the relationship is not exact, a general correlation between inequality and fear of crime. The lowest levels of inequality and fear of crime can be found in regions of Denmark and Switzerland (and also in Cantabria, Spain). The highest levels of both variables are in some regions in the UK (like London, the North West or the East Midlands), in Ireland's Mid-East and in Portugal (Lisbon).

It is also the case that there is a significant degree of regional variation within countries in Figures 5 and 6. Looking at inequality, there are stark differences between the South of England and Scotland or between Andalucia and Cantabria in Spain. Looking at fear of crime, the regional differences in Spain are again significant (but so are they in Sweden).

6 Model Results

Table 1 shows parameter estimates, standard errors, and 95% confidence bounds for our basic model estimating the effects of relative income, macro-inequality and their interaction. Because of the interaction, the interpretation of our variables of interest is not straightforward. We develop a stricter test of our argument below by calculating the specific effects of being rich or poor conditional on different levels of macro-inequality. Suffice it to say at this stage that these three variables are statistically significant. As expected, we find that income distance has a negative effect on redistribution preferences: the further someone is from the mean income, the more she opposes income redistribution. We also find that increasing income inequality goes hand in hand with higher preferences for redistribution, and that this relationship increases with an individual's income distance.

Although not the focus of this paper's analysis, the results in Table 1 also show some of the individual control variables to be significant determinants of redistribution preferences in a manner compatible with the existing literature. Older individuals and women are more in favor of redistribution, while those with higher education oppose it. Potential recipients of transfer payments – the currently unemployed – support income redistribution. Among social classes we find workers in favor of redistribution, something that also holds true for those individuals commanding high general skills, but not for those with specific skills. Among our regional level controls we find higher average support for redistribution in high unemployment regions, whereas regions specializing in high-tech display lower average levels of support.

To gain a more intuitive understanding of the role of inequality, we calculate average predicted probabilities for supporting redistribution among rich and poor individuals living in high or low inequality regions, respectively.[22] As before, we will

[22] "Simple" predicted probabilities are calculated by setting the variables in question to the chosen values (e.g., rich or poor in high or low inequality regions) while holding all other variables at one

Table 1: Income inequality and redistribution preferences. Maximum likelihood estimates, bootstrapped, multiple overimputation standard errors, and 95% confidence intervals.

Eq.: Redistribution	est.	s.e.	95% CI	
Income distance	−0.046	0.003	−16.390	−0.040
Inequality (Gini)	1.389	0.748	1.860	2.868
Distance*Gini	0.254	0.100	2.540	0.450
Age	0.010	0.005	1.950	0.019
Female	0.142	0.013	11.380	0.167
Education	−0.023	0.002	−9.860	−0.018
Unemployed	0.146	0.022	6.570	0.189
Not in labor force	−0.065	0.012	−5.240	−0.041
Household size	0.020	0.004	4.720	0.029
Self-employed	−0.079	0.018	−4.430	−0.044
Lower supervisor	0.042	0.013	3.330	0.067
Skilled worker	0.066	0.019	3.520	0.103
Unskilled worker	0.123	0.018	7.030	0.158
High general skills	−0.091	0.015	−6.020	−0.061
Specific skills	0.000	0.014	0.000	0.028
Percent foreigners	−0.226	0.350	−0.650	0.459
Unemployment rate	0.035	0.008	4.320	0.051
High-tech specialization	−0.085	0.036	−2.340	−0.014
Gross-domestic product	−0.059	0.040	−1.460	0.020
Test vs. M0	F=86.07, p=0.000			
Likelihood	−120,192			

Note: Estimates from equation (1). Multiple overimputation, bootstrapped standard errors based on 100 replicates from 129 regions and 14 countries. N=96,682. Wald test M0 is against null model without predictors. Estimated cut-points not shown. Distribution of test is based on Barnard and Rubin (1999). Likelihood value is averaged across imputations.

Table 2: Probability of support for redistribution among the Rich and the Poor in low and high inequality regions.

		Gini	
		low	high
Income	Poor	25.9	28.0
	Rich	17.3	22.5

Note: Calculated from equation (1). Average predicted probabilities. Region-county bootstrapped, multiple overimputation standard errors. All probabilities are significantly different from zero.

define rich and poor as the 90th and 10th percentiles of the income distribution. Similarly, high inequality will refer to Gini values at the 90th percentile of the regional distribution, while low inequality refers to the 10th. The results in Table 2 provide strong confirmation of our initial expectations. Among the poor the probability of strongly supporting redistribution remains at similar levels regardless of the level of inequality, changing only from 26 to 28 percent when moving from low to high inequality. In contrast, the effect of macro-inequality is more pronounced among the rich: explicit support for redistribution rises from 17 percent in low inequality regions to over 22 percent in high inequality areas. In other words, the difference in predicted support for redistribution due to increased inequality is more than twice as large among the rich.

To put this conclusion to a stricter test we calculate average marginal effects of income inequality for rich and poor individuals, shown in Table 3 together with their respective standard errors and 95 percent confidence bounds. The results further

observed value (e.g., the mean values). Average predicted probabilities, however, are calculated by setting the variables in question to the chosen values while holding all other variables at all their observed values. The final estimates are the average of these predictions. We do the same below when calculating average marginal effects. See Hanmer and Kalkan (2012) for a recent discussion of the advantages of these estimates in a political science context.

Table 3: Marginal effect of inequality for the rich and poor. Average marginal effects for predicted strong support of redistribution.

	Marginal effect of Gini			
	est	s.e.	95 % CI	
Poor	0.240	0.206	−0.165	0.646
Rich	0.571	0.250	0.076	1.066

Note: Calculated from equation (1). Region-county bootstrapped, multiple overimputation standard errors.

support our argument. The marginal effect of inequality among rich individuals is large and statistically different from zero. In contrast we find a considerably smaller marginal effect among the poor, with a 95 percent confidence interval that includes zero.

It is important to point out that the estimates in Tables 1-3 represent a significant amount of support for the relationship hypothesized in Figure 1. As we expected, redistribution preferences converge for the poor regardless of the macro-level of inequality. We also find the redistribution preferences of the rich to diverge as macro-inequality grows. Some influential alternative hypotheses are contradicted by our evidence.

An important literature posits that, in high inequality contexts, the poor are diverted from the pursuit of their material self-interest. This effect would imply that, in contradiction to Figure 1, redistribution preferences would diverge for the poor and converge for the affluent. Perhaps the most well-known example of these arguments is its application to the high inequality example of the US and the contention that second-dimension issues (particularly cultural and social ones) outweigh economics for the American working class.[23] More comparatively, Shayo's (2009) important

[23] See Frank (2004), the critique in Bartels (2006), and the comparative analyses by De La O and Rodden (2008) and Huber and Stanig (2011).

contribution to the political economy of identity formation follows a similar logic.[24] If these arguments were correct, we would expect the poor in unequal countries to be distracted from their material self-interested redistribution preferences, to the extent that these second-dimension concerns are correlated with macro-level inequality.[25] The results presented above suggest that the poor are not distracted from the pursuit of their present material self-interest in regions with higher levels of macro-inequality, whether because of second-dimension concerns or prospects of upward mobility.

In another theoretical alternative, Lupu and Pontusson (2011) propose that macro-levels of equality are related to empathy. They argue that, because of social affinity, individuals will be inclined to have more similar redistribution preferences to those who are closer to them in terms of income distance. While Lupu and Pontusson emphasize skew (rather than Ginis) and the position of the middle class, their argument implies that social affinity would make the rich have higher levels of support for redistribution as inequality decreases (the opposite of the predictions in Figure 1). A similar relationship would be expected by the approach that relates beliefs in a just world to redistribution preferences. To the extent that macro-levels of inequality are related to these beliefs (for example that inequality rewards the hard-working and punishes the lazy), we would observe lower levels of support for redistribution from

[24] Shayo's theoretical model emphasizes two identity dimensions: economic class and nationality. As a result of status differences, the poor are more likely than the rich to identify with the nation rather than their class in high inequality countries. Because they take group interests into account, moreover, the poor who identify with the nation are less supportive of redistribution than the poor who identify with their class.

[25] A similar expectation emerges from the "prospect of upward mobility" (POUM) hypothesis. Benabou and Ok (2001) argue that the poor do not support high levels of redistribution because of the hope that they, or their offspring, may make it up the income ladder. To the extent that mobility is correlated with macro-level inequality (something often argued in relation to the US but that is in any case emipircally not clear), we would expect a different relationship between income and preferences from that depicted in Figure 1.

the rich in countries with higher inequality and a higher normative tolerance for it (Benabou and Tirole 2006; Alesina and Glaeser 2004). Our evidence fails to support these arguments.

As we mentioned above, an influential literature in comparative political economy has argued that, if macro-inequality means that the rich are more likely to become poor, current generosity may not reflect non-economic concerns but the demand for insurance against an uncertain future (Moene and Wallerstein 2001; Iversen and Soskice 2009; Rehm 2009). To address this, we introduced an explicit measures of risk into the analysis. An important component of the demand for insurance and redistribution has to do with the risk of becoming unemployed. We operationalize risk as specific skills. Iversen and Soskice (2001) argue that individuals who have made risky investments in specific skills will demand insurance against the possible future loss of income from those investments. Our measure of skills (taken from Fleckenstein, Saunders, and Seeleib-Kaiser 2011) distinguishes among specific, high and low general skills and it is meant to capture this individual risk directly. We must mention that the effects of risk are not an issue of primary importance to our analysis, we are only interested in showing (as we do in the results above) that our findings are robust to the inclusion of these explicit measures of risk. Nevertheless, going back to Table 1, our evidence suggests individual-level skill specificity to be a statistically insignificant determinant of redistribution preferences.

In the previous sections, we went on to argue that the main mechanism linking inequality and redistribution preferences is fear of crime. Table 4 presents estimates from our simultaneous ordered probit model linking inequality to fear of crime, which then is expected to shape preferences for redistribution. In our fear of crime equation, we include a number of factors identified in the literature (e.g., Hale 1996) but we do not report them here for reasons of space (see online supplement Table S.2). Suffice it to say that we find, not surprisingly, that having previously been a victim of crime

Table 4: Fear of crime, relative income, inequality, and redistribution preferences. Maximum likelihood estimates, bootstrapped, multiple overimputation standard errors, and 95% confidence intervals.

Eq.: Fear of crime	est.	s.e.	95% CI	
Crime victim	0.279	0.021	0.238	0.321
Income distance	−0.017	0.003	−0.023	−0.011
Inequality (Gini)	4.806	0.697	3.414	6.199
Controls		included		
Eq.: Redistribution preferences				
Income distance	−0.063	0.004	−0.071	−0.054
Inequality (Gini)	0.541	0.802	−1.043	2.126
Income distance×Gini	0.218	0.094	0.033	0.404
Fear of crime	0.248	0.069	0.112	0.385
Income distance×Fear	0.011	0.002	0.006	0.015
Controls		included		
Error corr.		$\hat{\rho}=-0.186$, p=0.003		
Test vs M1		F=215.1, p=0.000		
Test $(\lambda, \rho) = 0$		F=15.5, p=0.000		
Likelihood		−224,589		

Note: System of equations (2) and (3). Region-county bootstrapped, multiple overimputation standard errors. N=96,682. Test M1 is against model without fear equation. Distribution of tests is based on Barnard and Rubin (1999). Estimates for τs and controls not shown; see S.2 for or full table. Likelihood value is averaged across imputations.

increases a person's fear of crime and that other variables affect fear of crime in the expected directions. More importantly, the results in Table 4 show that, in agreement with our argument, in regions with higher levels of inequality, respondents – whether rich or poor – are more afraid of crime.

Turning to the redistribution equation in Table 4, we find clear evidence that fear of crime matters for redistribution preferences. Individuals who are more afraid of crime show higher levels of support for redistribution, a relationship that is slightly stronger among those with higher incomes. A test for independence of fear of crime and redistribution equations is rejected (F=16.7 at 2df.). We also find that the direct effect of macro-inequality becomes statistically insignificant once we explicitly estimate the effect of fear of crime.

Again, a stricter test of our hypotheses can be obtained by calculating average

Table 5: Effects of fear of crime and inequality among the rich. Average marginal effects for predicted strong support of redistribution.

	Marginal effect among rich			
	est	se	95% CI	
Fear of crime	0.099	0.030	0.040	0.157
Gini	0.321	0.266	−0.205	0.847

Note: Calculated from eqs. (2) and (3). Region-county bootstrapped, multiple overimputation standard errors.

marginal effects. We expect to find (i) a significant (both in the statistical and substantive sense) marginal effect of fear of crime on redistribution preferences, and (ii) that the size of the remaining effect of macro-inequality (operating through other channels) is reduced. Table 5 shows average marginal effects of fear of crime and inequality among the rich. As already indicated by our coefficient estimates, the marginal effect of fear of crime is strong and clearly different from zero. More importantly, we find the remaining marginal effect of inequality to be greatly limited. In fact, it is reduced to such an extent that its confidence interval includes zero. This result does of course not negate the existence of other relevant channels linking inequality and preferences, but it at least signifies that externalities go a long way in explaining the effect of inequality on redistribution preferences.

7 Robustness and placebo tests

While the previous section is quite convincing at providing support for our hypotheses, there are alternative arguments in the existing literature with implications about the relationship between income and redistribution preferences that are connected to the ones proposed in this paper. These alternative explanations rest on very different causal claims that we can test directly. These tests are reported in Table 6, focusing on our variables of interest, the marginal effects of Gini and fear of crime for the rich.

Existing levels of redistribution. Previous research indicates that average support for redistribution tends to fall when the existing levels of redistribution are high. The idea that there is some threshold at which the disincentives effects of redistribution become more severe (see for example Tanzi and Schuhknecht 2000) provides a possible explanation for this relationship. Arguably, people who live in countries with large redistributive welfare states are more concerned about, and more aware of, the disincentive effects of redistribution. It also seems likely that some respondents take actual levels of redistribution into account when expressing their preferences, i.e., that they are expressing agreement or disagreement with the proposition that the government should do more to reduce income differences. In an alternative, but related, explanation, high levels of redistribution are argued to be connected with encompassing welfare and labour market institutions which provide the poor and the rich with more information about redistributive issues (see Kumlin and Svallfors 2007). This would imply more extreme redistribution preferences by poor and rich in high welfare state countries.

To test these alternatives, we include regional levels of social spending in our estimation. We calculate spending levels by weighting national (ppp-adjusted) per capita social expenditure by the regional share of the recipient population.[26] What constitutes this population can be calculated from our available survey data as the population share of unemployed, the disabled, and those in retirement. The results in Table 6 show that inclusion of pre-existing redistribution reduces the direct effect of inequality in the model with endogenous fear even further, but leaves our core result – the role of fear of crime – virtually unchanged.

[26] Spending data are total public social spending (in cash and in kind), per head, in constant 2000 prices and PPP US dollars from OECD's SOCX database. The main social policy areas covered are: Old age, Survivors, Incapacity-related benefits, Health, Family, Active labour market programmes, Unemployment, and Housing.

Table 6: Overview of robustness checks. Average marginal effects among the rich from simple model and model including fear of crime. Estimates whose 95% confidence interval includes zero are marked with †.

	Simple model		Model with endogenous fear			
	Gini		Fear		Gini	
Robustness tests	Est	s.e.	Est	s.e.	Est	s.e.
(1) Social spending	0.555	0.253	0.101	0.029	0.301	0.252†
(2) Pre-crisis years	0.574	0.251	0.092	0.031	0.343	0.257†
(3a) Population density	0.569	0.257	0.098	0.032	0.332	0.260†
(3b) Urban area	0.568	0.254	0.097	0.029	0.321	0.258†
(3c) Urban region	0.557	0.242	0.104	0.029	0.296	0.247†
(4) Religion	0.490	0.237	0.101	0.027	0.236	0.246†
(5a) Ideology (redist. eq)	0.585	0.245	0.097	0.025	0.337	0.245†
(5b) Ideology (both eq.)	0.585	0.245	0.098	0.028	0.333	0.252†
(6) Wage earner sample	0.601	0.265	0.112	0.031	0.317	0.266†
Placebo test			Ideology		Gini	
(7) Ideology instead of fear			−0.076	0.004	0.588	0.241

Note: Multiple over-imputation, boostrapped standard errors (100 replications).

Pre-crisis years One might argue that survey interviews conducted in late 2008 are affected by the onset of the global economic downturn. To check for this possibility we drop this entire wave from our analysis and use only interviews conducted before 2008. Results in 6 show that this does not affect our results.

Population density/urbanization. Although our analyses emphasize the regional level, one may argue that we ignore political geography, i.e., the distinct preferences of individuals living in high-density, urban areas (see, for example, Cho, Gimpel, and Dyck 2006). As argued by Rodden (2010: 322), it is clear that individuals sort themselves into neighborhoods with similar demographic, occupational, income, and ultimately political preferences. We address this concern in two ways. First, we simply include an individual-level survey variable, which indicates if the respondent lives in an urban region. Second, we construct regional variables measuring the degree of urbanization of a region (this is simply the regional mean of our individual level variable) and population density (data from Eurostat). Table 6 shows that both individual and contextual measures do not change our core results.

Religion. Previous research has stressed the role of religion for redistribution preferences (Scheve and Stasavage 2006; Stegmueller et al. 2012). We expect religion to have an additional effect, largely unconnected to the inequality—preferences nexus. Here we find a somewhat reduced effects of inequality among the rich, but it is still significant (its confidence interval excludes zero).[27] Similar to our previous checks, results in Table 6 confirm that including fear of crime substantially reduces the remaining effects of inequality.

Ideology. Our main analyses exclude a measure of ideology or left-right self-placement, since we believe that explaining economic preferences helps us understand a key constituent of ideology and therefore it should not be an 'explanatory' variable in our model. Nonetheless, it has been argued that ideological positions are an independent source of redistribution preferences (see Margalit 2011) and we can show that the inequality—fear link is robust to the inclusion of this variable. In Table 6, we account for respondents' ideology in two ways. First, we simply include ideology in our redistribution equation and find the results unchanged. Second, we allow for the fact that conservative respondents might be more likely to indicate fear of crime, by including ideology in our fear of crime equation. Again, we find our results confirmed.

Placebo test. We also conducted a placebo analysis. One may argue that the inclusion of any variable measuring political perceptions or beliefs could render the macro effect of inequality insignificant. To check for this possibility we replace our theoretically important variable, fear of crime, with the 'catch-all' ideology variable. We find in Table 6 that, as expected, ideology does shape redistribution preferences. However, unlike in our main models, the effect of inequality is significant and not

[27] Note that the difference in marginal effects between the rich and poor (0.32) is still highly relevant (s.e.=0.14).

reduced in magnitude at all, indicating that this alternative political variable does not contribute to explaining the effect of inequality.[28]

8 Conclusion

It is appropriate to conclude this paper by re-emphasizing the importance of our main results and exploring some of their implications for further research. We have shown above that the association between macro-inequality and redistribution preferences proposed in our main argument is extraordinarily robust. The evidence demonstrates that for the poor non-pocketbook concerns are trumped by immediate disposable income incentives and that redistribution preferences converge regardless of the macro-level of inequality as income declines. By contrast, macro-inequality promotes concerns for its negative externalities only for the rich. We showed that the redistribution preferences of a rich individual in a low income region differ starkly from those in a high inequality region and that this difference is motivated by fear of crime.

In some ways, this is a profoundly unintuitive result (the rich are more supportive of redistribution in those regions where inequality is highest). We do provide an intuitive solution for this puzzle (the concern for crime by the rich) but it is germane to ask whether our results emerge from the idiosyncrasies of our particular sample. We have mentioned before that the rich, if concerned about the externalities of inequality, could do (at least) two things: reduce inequality through redistribution, or reduce its potential consequences by demanding more protection (policing, incarceration, etc). We have argued that demands for redistribution and protection can be complementary, but it is tempting to think that the rich in Western Europe may be more likely than the rich in other regions to think of redistribution as a good option. While this is a topic

[28] Further robustness checks (not shown here) such as inclusion of time fixed effects, sector of employment, or income source, again yield the same results.

we hope to do further research on, we will mention that our findings connect with a significant literature of the consequences of inequality in the US. Using American data, Gelman et al. (2008) find, like us, that the poor (whether in Connecticut or Mississippi) are quite similar. It seems to be the case that it is the rich who are responsible for some of the aggregate political differences we see (in Western Europe as well as the US). And this is perhaps the most important take-home message in our paper.

Going back to the unintuitive nature of our findings, one might finally ask why we do find less redistributive systems in precisely the places where the rich are more supportive of redistribution. We think this is an important question in need of a significant amount of further research. As McCarty and Pontusson (2009) note, models of the political economy of redistribution involve two separate propositions: a "demand-side" proposition, concerning the redistribution preferences of voters, and a "supply-side" proposition, concerning the aggregation of these preferences. In this paper we have focused on the first proposition and ignored the second. We hope that the arguments in this paper clarify the role of preferences as an essential first step for an accurate understanding of the supply of redistribution.

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Table S.1: Descriptive statistics

Continuous	mean	sd
Income distance	0.00	26146
Age [years]	48.45	17.68
Education [years]	12.15	4.29
Household member	2.59	1.35
Regional high-tech specialization	0.14	1.01
Regional GDP [per capita]	26919	6894
Regional Gini	0.33	0.03
Foreigners [% in region]	6.58	5.77
Unemployment [% in region]	6.50	3.44
Dichotomous		
Unemployed		4.5%
Not in labor force		17.1%
Female		53.0%
Crime victim		20.1%
Self-employed		8.1%
Lower supervisor		20.2%
Skilled worker		10.2%
Unskilled worker		22.7%
High general skills		37.2%
Low general skills		34.6%
Specific skills		20.3%

Note: Based on five multiply imputed data sets, ESS 2002-2008.

Table S.2: Fear of crime, relative income, inequality, and redistribution preferences.

Eq.: Fear of crime	est.	s.e.	95% conf. int.	
Crime victim	0.279	0.021	0.238	0.321
Income distance	-0.017	0.003	-0.023	-0.011
Inequality (Gini)	4.806	0.697	3.414	6.199
Age	0.063	0.005	0.054	0.073
Female	0.588	0.019	0.550	0.626
Education	-0.014	0.003	-0.020	-0.008
Unemployed	0.098	0.026	0.046	0.149
Not in labor force	0.071	0.014	0.043	0.099
HH size	-0.025	0.006	-0.036	-0.013
Self-employed	-0.062	0.024	-0.108	-0.016
Lower supervisor	0.100	0.014	0.073	0.127
White collar	0.185	0.019	0.148	0.222
Blue collar	0.128	0.018	0.093	0.163
Percent foreigners	1.270	0.715	-0.131	2.671
Gross-domestic product	-0.120	0.048	-0.215	-0.026
Eq.: Redistribution				
Income distance	-0.063	0.004	-0.071	-0.054
Inequality (Gini)	0.541	0.802	-1.043	2.126
Income distance*Gini	0.218	0.094	0.033	0.404
Fear of crime	0.248	0.069	0.112	0.385
Income distance*Fear	0.011	0.002	0.006	0.015
Age	0.000	0.006	-0.012	0.013
Female	0.042	0.033	-0.022	0.106
Education	-0.020	0.002	-0.025	-0.016
Unemployed	0.126	0.024	0.080	0.172
Not in labor force	-0.077	0.014	-0.104	-0.049
HH size	0.024	0.004	0.016	0.033
Self-employed	-0.068	0.017	-0.102	-0.035
Lower supervisor	0.026	0.014	-0.002	0.055
Skilled worker	0.038	0.023	-0.007	0.083
Unskilled worker	0.104	0.020	0.065	0.143
High general skills	-0.087	0.015	-0.117	-0.057
Specific skills	0.001	0.015	-0.028	0.030
Unemployment rate	0.034	0.008	0.019	0.050
High-tech specialization	-0.084	0.040	-0.162	-0.007
Percent foreigners	-0.040	0.043	-0.124	0.043
Gross-domestic product	-0.423	0.431	-1.268	0.423
Error corr.	$\hat{\rho}=-0.186$, p=0.003			
Test vs M1	F=215.1, p=0.000			
Test $(\lambda,\rho)=0$	F=15.5, p=0.000			
Likelihood	$-224{,}589$			

Note: System of equations (2) and (3). Robust, multiple imputation standard errors clustered by 129 regions and penalized for 5 imputations (Rubin 1987). N=96,682. Test M1 is against model without fear equation. Distribution of tests is based on Barnard and Rubin (1999). Likelihood value is averaged across imputation.