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MODELLING HETEROGENEOUS PREFERENCES FOR INCOME REDISTRIBUTION–AN APPLICATION OF CONTINUOUS AND DISCRETE DISTRIBUTIONS

BY CHRISTIAN PFARR* and ANDREAS SCHMID

University of Bayreuth

AND

MORTEN RAUN MØRKBAK

University of Southern Denmark

This paper investigates observable and unobservable heterogeneity in individuals' preferences for redistribution—differentiating the desired overall volume of redistribution and who should receive benefits, subsidies, or transfers. We use data from a discrete choice experiment (DCE) conducted in the field and based on a representative sample of the German voting-age population. Applying random parameters and latent class models, our results show that latent and potentially discontinuously distributed factors must be accounted for, as they heavily impact the interpretation of the findings. We find considerable heterogeneity in redistribution preferences, clearly identifying three distinct subgroups. While all groups are in favor of redistribution, they differ regarding the preferred allocation of the redistributive budget.

JEL Codes: C93, D31, H23

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1. INTRODUCTION

Knowledge of citizens' preferences matters for governing and social stability (Foley and Edwards, 1996; Richardson, 2000). Since preferences are an individual matter, heterogeneity is to be expected. Most empirical approaches elaborating on this heterogeneity require a priori knowledge and selection of key variables that are assumed to affect observable heterogeneity (Boxall and Adamowicz, 2002). This implies a restriction to only few determinants, such as socio-demographic characteristics. However, individuals' expressed preferences are also affected by

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*Correspondence to: Andreas Schmid, University of Bayreuth, Health Management, Universitätsstraße 30, D-95447 Bayreuth, Germany. (andreas.schmid@uni-bayreuth.de).

unobservable (latent) characteristics (McFadden, 2001). The neglect of latent factors in analyses of preference heterogeneity might explain some of the inconclusive evidence found in the literature (e.g. Fong, 2001; Alesina and La Ferrara, 2005; Alesina and Giuliano, 2011). For example, in the context of preferences for redistribution in the U.S., Alesina and Giuliano (2011) show a positive effect of age, while Alesina and La Ferrara (2005) find a negative one. Fong (2001) cannot find any effect.

We investigate individuals' preferences for redistribution—specifically, their desired overall volume of redistribution and their preferences about who should receive benefits, subsidies, or transfers. We use data from a discrete choice experiment (DCE) that was conducted in the field and based on a representative sample of voting-age Germans. The data was collected in 2012 specifically for the analysis of preferences for redistribution. The framework enforces trade-offs and budget constraints on the participants. In analyzing the data, we use several models to simultaneously account for both observable and unobservable factors affecting preferences. It is very likely that in many instances heterogeneity of these preferences is not distributed continuously. This is for example the case, if two subgroups with antipodal preferences exist within one age group—one favoring higher redistribution the other favoring lower redistribution—and no observable characteristics are available to identify the subgroups. For this reason, we allow for potentially discrete and continuous variation of unobservable factors using latent class and random parameter models. In the further analyses, we obtain willingness-to-pay values that allow us to compare the strength of preferences across the groups identified in the latent class model and with respect to different types of recipients.

Our goal is twofold. First, we aim to demonstrate the relevance of observed and unobserved heterogeneity in public economics. Latent class models can identify subgroups without having to rely exclusively on observable factors. They overcome the restrictions of most commonly applied models, which assume continuous distributions of latent characteristics. In combination with a DCE that enforces trade-offs and budget constraints, our approach should also prove useful in related fields such as the analysis of interest groups and political economics in general. Second, by applying this approach to preferences for income redistribution, we offer additional explanations and insight into individuals' preferences for redistribution and contribute to the already existing but inconclusive literature on preferences for redistribution. For a comprehensive review, see Alesina and Glaeser (2004). The combination of our method and data allows for the detailed analysis of preference structures beyond the scope of prior studies such as those by Alesina and Giuliano (2011), Neustadt and Zweifel (2011) and Pittau *et al*. (2013) that analyzed preference heterogeneity based on observable sociodemographic characteristics.

We identify three distinct latent groups of subjects who can be characterized by their preferences for redistribution and group characteristics. Besides expected differences between observable characteristics—such as retirees vs. families with children—we find surprising heterogeneity within some of these sociodemographic categories that may indicate a discrete distribution of unobserved factors.

The remainder of the paper is organized as follows. The next section describes in more detail our contribution in the context of the literature. Section 3 explains the background as well as the econometric features of DCEs and introduces latent class models. Section 4 discusses the design and the implementation of the field experiment, and Section 5 presents the results. Section 6 concludes.

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2. Literature

The literature on preferences for redistribution is vast. The *theoretical* foundations are, to a large extent, provided by the work of Romer (1975), Roberts (1977), and Meltzer and Richard (1983), focusing on individuals' utility derived from their income and on the median voter. This literature is the starting point for most models that incorporate other factors, such as past or expected social mobility and inequality or fairness considerations. Alesina and Angeletos (2005) and Benabou and Tirole (2006) provide more recent models that account, at least partly, for how the interplay of behavioral factors and economic rationality might help to explain heterogeneous preferences for redistribution.

The related *empirical* evidence is mixed, mostly because numerous factors drive the results. Overall, empirical studies on preferences for redistribution at the micro level[1] can be categorized by the determinants they examine, the aims of redistribution, and the method used to elicit preferences.

Studies investigating individual-level determinants focus mostly either on economic factors, such as income and social status (e.g. Alesina and La Ferrara, 2005; Alesina and Giuliano, 2011), behavioral factors, such as beliefs regarding the role of luck and effort in life outcomes (e.g. Fong, 2001, 2006; Alesina and Angeletos, 2005; Alesina and La Ferrara, 2005), altruism (e.g. Andreoni and Miller, 2002; Fong *et al*., 2006; Fong and Oberholzer-Gee, 2011), or religion (e.g. Benabou and Tirole, 2006; Gruber and Hungerman, 2007). While all of these studies consider specific determinants of redistribution while controlling for other aspects, some of them examine more general relations between redistribution and socio-demographic characteristics such as employment status, education, age, gender, and race. Alesina and Giuliano (2011) and Guillaud (2013), for example, cover family structures and gender, and Fong (2001) and García-Valiñas *et al*. (2008) elaborate on the educational background of voters. However, none of these studies accounts for potentially discrete variation of unobservable factors.

Regarding different aims of redistribution, in almost all of these studies, data is usually gathered through survey questions, such as "To what extent 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

[1]Macro-level analyses of the effects of income (e.g. Fields and Ok, 1999; Karabarbounis, 2011), of inequality and growth (e.g. Alesina and Rodrik, 1994), of the role of political institutions such as different electoral systems (e.g. Milesi-Ferretti *et al*., 2002; Persson and Tabellini, 2003; Feld *et al.*, 2010), or the role of political parties (e.g. Perotti and Kontopoulos, 2002) are of limited relevance to our study, as we aim to explore preference heterogeneity at individual level within a country. The same is true for studies that relate to the effect of ethno-linguistic fragmentation on preferences for redistribution (e.g. Fong, 2006; Luttmer and Singhal, 2011; Alesina *et al.*, 2012).

with low incomes'?" (e.g. Alesina and La Ferrara, 2005; Pittau *et al*., 2013). Furthermore, such survey questions capture attitudes, that is, some degree of favor or disfavor, rather than preferences as defined by microeconomic theory (Eagly and Chaiken, 1996; Kahneman *et al*., 1999). This sort of question conflates redistribution and the size of government, combining redistribution and social insurance[2] without differentiating according to redistributive goals or recipients. We argue that differentiating the aims is necessary to explain heterogeneous preferences, since the interaction of the aims and observable as well as unobservable socio-demographic characteristics is expected to determine someone's expectation of personal utility regarding the effects of a change in the redistribution. Moreover, such simple survey questions cannot capture trade-offs, such as budgetary constraints. Hayo and Neumeier (2014) address this problem in a study related to Germany by imposing a public budget constraint. However, the scope of their study differs from ours. They focus on attitudes about public spending in general, including categories such as defense or public safety and thus obscure the explicit link to redistribution.

Laboratory experiments are another way to deal with these challenges. Much of this broad strand of literature related to preferences for redistribution is based on the works on inequality aversion by Fehr and Schmidt (1999), Bolton and Ockenfels (2000) or Charness and Rabin (2002).[3] By implementing according study protocols researchers can model scenarios to test very specific hypotheses under controlled conditions, e.g. regarding role of risk aversion, altruism or fairness. For example, Durante *et al*. (2014) disentangle the relative importance of self-interest with other influences such as the insurance motive and social preferences. Yet, the authors also conclude that their results rely on a sample of undergraduate students, which cannot be directly extrapolated to "the real-world economy" (p. 1085) and stress the benefit of complementing research methods.

Some studies try to overcome these problems while providing explanations for real-world redistributive outcomes by implementing choice-based experiments in field surveys. Boeri *et al*. (2001, 2002) use contingent valuation, which enforces some trade-offs—especially regarding the price of the good—but does not account for trade-offs between remaining characteristics (Mitchell and Carson, 1989; Bateman *et al*., 2002). However, investigating the shares of redistribution dedicated to different recipient groups requires an approach that enforces trade-offs between all characteristics. A method able to do that is discrete choice experiments (DCEs), which present respondents with hypothetical choices. Besides explicit trade-offs between all characteristics, this approach also implements a budget constraint (Louviere and Lancscar, 2009; for more details on DCE see section 3 and 4). It is rooted in microeconomic theory and thus enables the approximation of preferences in terms of willingness to pay rather than just attitudes (Bateman *et al*., 2002).

[2]Alesina and Giuliano (2011) point out that the two core objectives of the welfare state—redistribution from the rich to the poor and the provision of social insurance—are difficult to disentangle. But the authors argue that, as they are close correlates, from an empirical point of view, this is not fatal. While being appropriate in most cases, this is of limited help if preference heterogeneity is to be analyzed in more detail.

[3]For a comprehensive review see Cooper and Kagel (2013).

Pfarr (2013), Neustadt and Zweifel (2015), and Pfarr and Schmid (2016) have implemented DCEs to study redistribution. The first two papers analyze different theory-based determinants for redistribution preferences, such as current and expected income. The third study tests the relevance of the income-health nexus in the context of redistributive social health-insurance systems. Neustadt and Zweifel (2011) also try to illuminate preference heterogeneity by separately examining the effects of age, employment, and health status in Switzerland. They hypothesize that an insurance motive explains most of the preferences—for example, retired people strongly support redistribution towards the elderly. None of their hypotheses are strongly supported by the results. We argue that this could be driven by the isolated analysis of single observable factors. It is quite likely that there are two or more distinct groups of retirees who can hardly be summarized by one joint distribution.

Our study represents the first attempt to analyze preference heterogeneity, accounting for different redistributive aims, while also allowing for observable as well as unobservable heterogeneity in the deterministic part of the utility function. We consider various determinants focusing on socio-demographic characteristics and, by virtue of data from a DCE, analyze them in direct relation to the volume and the allocation of the redistributive resources. Applying latent class models as well as standard multinomial logit and random parameters logit models allows us not only to account for variation from observable and unobservable characteristics. We also account for discrete factor variation and are able to approximate the composition and the size of these latent groups. Thus we add to the literature by overcoming methodological challenges of prior studies, expanding the evidence on preference heterogeneity by giving insights into the structure of the heterogeneity.

3. Methods

Preferences for redistribution are difficult to measure. Redistribution is not traded in real economic markets, and preferences are not revealed or observed directly. In such cases, *stated preference* techniques can help identify preferences (Louviere *et al*., 2000). We apply a DCE to capture preferences for redistribution. This concept is consistent with traditional microeconomics, which treats preferences as a latent construct revealed by choices. Within a choice experiment, individuals decide between at least two alternatives. Each alternative—in our case, redistribution schemes—exhibits the same attributes (i.e. characteristics defining the good) but varies regarding attribute levels (i.e. the quantity of each attribute). Thus, as a result of utility maximization, the chosen alternative must be the one contributing the highest utility.

The underlying theory of DCE is based on Lancaster's consumer theory (Lancaster, 1966) and random utility theory (Luce, 1959; McFadden, 1974). In Lancaster's theory, consumer preferences are defined in relation to bundles of characteristics, and the demand for goods is a derived demand. Consumption involves extracting characteristics from goods (Gravelle and Rees, 2004). The model applied in the parametric analysis of responses is a mixed logit model, which can be derived in a number of different ways (see Hensher and Greene, 2003; Train, 2009). The point of departure is a model formulation that incorporates an error component. Following Scarpa *et al.* (2005), an alternative specific constant (ASC) is specified for the status quo alternative to capture the systematic component of a potential status quo effect. An error component, in addition to the usual Gumbel-distributed error term, is incorporated to capture any remaining status quo effects in the stochastic part of utility. The error component, μ, which is implemented as a zero-mean normally distributed random parameter, is assigned exclusively to the status quo alternatives. Thus it captures any additional variance associated with the cognitive effort of evaluating the status quo alternative relative to the experiment's hypothetical alternatives—positive or negative (Brownstone and Train, 1998; Herriges and Phaneuf, 2002; Scarpa *et al.*, 2005; Scarpa *et al.*, 2008). This results in the following general utility structure:

$$U_{ntj}=\begin{cases} V(ASC, x_{ntj}, \beta, \mu)+\varepsilon_{ntj}, & j=1 \text{ (status quo alternative)} \\ V(x_{ntj}, \beta) \qquad\qquad +\varepsilon_{ntj}, & j=2 \text{ (hypothetical alternative)} \end{cases} \tag{3.1}$$

where the indirect utility, V, is a function of the vector of explanatory variables, x_{njt}, and associated parameters, β. For the status quo alternative, the error component μ enters the indirect utility function, while it is restricted to zero for the experiment's policy alternative. The unobserved error term ε_{ntj} is assumed iid extreme-value distributed. The individuals are denoted by n, while j is the alternative and t is the choice set. The conditional logit model defines the probability of an individual n choosing alternative k out of j alternatives:

$$P_{ntk}=\frac{e^{\lambda\beta' x_{ntk}}}{\sum_j^J e^{\lambda\beta' x_{ntj}}} \tag{3.2}$$

where β' is a vector of all betas, λ is the scale parameter, which is typically normalized to unity and cancels out when examining ratios such as willingness to pay (WTP) (see below). Following Scarpa *et al.* (2005) andTrain (2009), the probabilities of the error component mixed logit model can be described as integrals of the standard conditional logit function evaluated at different μ's with a density function as the mixing distribution. This specification can be generalized to allow for repeated choices by the same respondent (that is, a panel structure) by letting z be a sequence of alternatives, one for each choice occasion, $z=\{z_1,\ldots,z_T\}$. Thus the error component coefficient may vary over people but is constant over the T choice occasions for each individual. The marginal choice probability then becomes:

$$P_{nkz}=\int\left(\prod_{t=1}^{T}\left[\frac{e^{\lambda\beta' x_{ntk}}}{\sum_j^J e^{\lambda\beta' x_{ntj}}}\right]\right)\varphi\left(\mu|0,\sigma^2\right)d\mu \tag{3.3}$$

where $\varphi\left(\mu|0,\sigma^2\right)$ is the normal density distribution function for μ.

We elaborate on this model by taking preference heterogeneity for program attributes into account with the introduction of a mixed logit model, the random parameter logit model (RPL):

$$P_{nkz} = \int \left(\prod_{t=1}^{T} \left[\frac{e^{\lambda \beta' x_{ntk}}}{\sum_{j}^{J} e^{\lambda \beta' x_{ntj}}} \right] \right) f(\beta | b, \eta) d\beta \tag{3.4}$$

where f is the density distribution function for β with a mean of b and a standard deviation of η. This model also holds the error-component specification, in the case where $\mu = \beta_{\mu} \sim f(\mu | 0, \sigma^2)$. In this case, all program attributes and the error component are assigned to follow a normal distribution, thus allowing for both positive and negative preference estimates. By applying the RPL model, we consider unobserved heterogeneity while, by definition, assuming continuous distribution. For further detail of the RPL model see e.g. Train (2009).

Finally, we examine whether the true distributions of some of the coefficients are better explained by using more flexible distributions, which do not necessarily match a convenient mathematical form (see Wedel *et al.*, 1999; Hess *et al.*, 2007). This implies that heterogeneity might not necessarily be distributed continuously. Instead, discrete distributions might be a better fit to the data. By applying a latent class (LC) specification, we can avoid the issue of predefined statistical distributions as in the mixed logit case (the RPL model), and at the same time control for both observable and unobservable heterogeneity in the deterministic part of the utility function (Hensher and Greene, 2003). By doing this the model also allows insights into the composition of the different segments by linking covariates to each class. Instead of using a continuous mixture distribution as above, we separate the heterogeneity by applying a latent class logit specification. The unconditional choice probability for alternative k and individual n is given by:

$$P_{nkz} = \sum_{s=1}^{S} \pi_S \prod_{t=1}^{T_n} \frac{e^{\lambda \beta' x_{ntk}}}{\sum_{j}^{J} e^{\lambda \beta' x_{ntj}}} \tag{3.5}$$

where S is the number of classes, π_s is the probability that individual n belongs to class s, and $P_n(k | \beta_s)$ is the probability of individual n choosing alternative k conditional on individual n being in class s.

Equation (3.5) assumes the same probability for the scale classes across all of the taste classes, implying that the scale is confounded within the estimated beta parameter. To avoid the issue of scale when comparing marginal utilities, we instead examine marginal rates of substitutions, so that the scale parameter λ from equation (3.2) cancels out; thus we can compare estimates across classes. Since the indirect utility function is linear in price, the marginal willingness to pay (MWTP) for the attribute is the ratio between the parameter of the attribute and the price parameter, such that:

$$MWTP_s = -\frac{\text{Attribute parameter}}{\text{Price parameter}} \tag{3.6}$$

Moreover, in the interpretation of the results, we consider both the program attributes in terms of MWTP and determinants of class membership. Class membership is determined by socio-demographic variables. The inclusion of these was based on a priori expectations, which we will elaborate on below. Finally, to avoid algorithm-specific artifacts, we used the software package NLOGIT (Hensher *et al.*, 2015) as well as the gllamm command in Stata 13 (Rabe-Hesketh *et al.*, 2004, 2005) to estimate the econometric models. The results are identical, no matter which software tool was used.

4. Implementation and Data

4.1. *Design and data presentation*

The hypothetical nature of DCEs requires the incorporation of the relevant attributes affecting individuals' utility and choices, respectively. Following Bateman *et al*. (2002), the setup of the DCE—including the selection of relevant attributes, the assignment of meaningful attribute levels, and the application of an experimental design to create a manageable number of choices—was developed based on the literature, expert interviews, group discussions, and paper-based pretests involving 629 students and faculty members. Finally, the DCE setup was tested in three independently conducted pretests with about 40 participants each. The last group was sampled in the pedestrian area of a large German city.

To simplify the experiment, the German social service budget, which summarizes all social spending, including public and social insurance spending, served as a starting point for the selection of relevant attributes. This budget has one major advantage: all dimensions of redistribution are merged into a limited number of categories reflecting different beneficiaries of redistribution. We chose a number of potential attributes based on this source, which were then revised during the process sketched out above. During this process, it turned out that participants focused on specific recipient groups rather than redistributive channels.

In the end, we singled out 10 attributes, which were grouped together in four diagrams to reflect their substitutive character and to make trade-offs explicit. First, the price attribute is the *personal tax and social insurance contribution* individuals must pay out of their monthly gross income. Second, the level of redistribution is measured as percentage of GDP. Third, five attributes reflect the socio-demographic status of beneficiaries (i.e. sick persons and persons in need of care, families with children, retirees, unemployed, working poor). Finally, the fourth group covers the nationality of the recipients (i.e. German, West European, other).

The second step incorporates the assignment of attribute levels. These should be realistic and sufficiently distinct to force respondents to trade off the different attributes and levels (Bateman *et al.*, 2002; Telser, 2002). To begin with, we chose the levels of the status quo based on official statistics, following the German social service budget for each attribute. Similarly realistic levels were assigned for

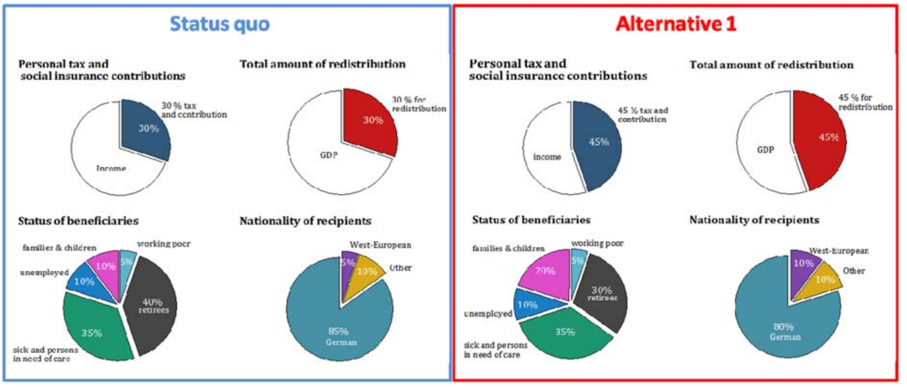

Figure 1. Choice situation.

each attribute. Table A.1 in the appendix presents the chosen attributes and their respective levels, categorized by their substitutive relationship.

The complete factorial design, containing all possible combinations of attributes and their levels, resulted in 129,600 combinations (alternatives), which could not be incorporated in an experiment. Accordingly, we applied a D-optimal fractional factorial design (see Kuhfeld *et al.*, 1994; Kanninen, 2002;, Kuhfeld, 2006), resulting in 49 unique alternatives. As this number of alternatives still exceeded the mental burden respondents could handle (see, e.g. Bech *et al.*, 2011), the number of choice tasks was further split into seven blocks, with each block consisting of seven choice sets. To test for consistency of choices and to evaluate whether the respondents meet the axiom of complete preferences, we included one of the choice sets twice. The decisions for the second identical alternative were not included in the empirical investigation. Each choice set consisted of a fixed status quo and a hypothetical redistributive scheme. Comparing a fixed status quo with an alternative ensures that comparisons of utilities always refer to an identical reference point. Respondents were randomly assigned to one of the seven blocks. Each block was composed to include a wide and balanced range of possible alternatives, i.e. covering alternatives with high and low levels of redistribution, tax etc. This ensures that the assignment to one of the seven blocks has no implications for our empirical results.[4]

4.2. *Administration of the Survey*

Figure 1 shows one of the final choice tasks. The alternative representing the status quo was placed on the left side. On the right side, an alternative offering a hypothetical redistributive scheme, which differed in one or more attribute levels, was presented. Respondents could compare the options and check which they preferred.

[4]Testing whether the exclusion of one of the seven blocks affects our main results supports the robustness of our findings.

The DCE and a complementing questionnaire were administrated in the field by the market research institute GfK Nuremburg. Participants were recruited using a national quota sample[5] of the German voting-age population and interviewed with computer assistance. This ensured that respondents could not jump back and forth between choice tasks and helped to reduce the complexity of the experiment.

In the first part of the interview, socio-demographic characteristics and attitudes towards different aspects of redistribution were collected. The second part gave the respondents a comprehensive description of the structure and size of the German welfare state (see online appendix) to obtain unbiased estimates and ensure that all participants had common knowledge. About one-quarter of the interview was been spent on this aspect. All attributes and their corresponding levels were introduced consecutively. Participants were instructed that the hypothetical redistributive schemes might be implemented in the future, asking them to decide which one they would choose if only the status quo alternative and the hypothetical alternative existed. To avoid learning effects, two warm-up decisions were included in the description. Following this and a chance to ask clarifying questions, the seven choice-tasks were consecutively presented. After the participants made their decisions, more sensitive information such as participants' income and questions for further robustness tests was collected. It took the participants about 36 minutes on average to answer the questions and complete the choice tasks. Respondents were provided with an in-kind acknowledgement upon completion.

4.3. *Data and class membership variables*

The data consisted of 1,538 Germans of voting age, which was representative across the general socio-demographic characteristics; Table A.2 in the appendix compares some selected items from the dataset with data from official statistics. The presented mean values of these items do not differ significantly from each other, indicating a high degree of representativeness.

The dependent variable in our models is the binary variable *choice*, reflecting an individual's decision for the status quo (zero) or a hypothetical redistributive scheme (one). With a mean value of 0.35, about one-third of the decisions favored a hypothetical redistributive scheme. The consistency check reveals that 13 percent of respondents failed to pick the same option in two identical scenarios. This is a fairly low number compared to similar studies (Phillips *et al.*, 2002), suggesting that the choice task was well explained to and understood by the participants.[6] We select a set of four socio-demographic characteristics, the so-called class membership variables (see Table A.3 in the appendix). These variables are used to support the identification of latent groups and are chosen to reflect the five beneficiary groups.

[5]Quota samples, as an equal alternative to random sampling, are frequently applied in social science research (ESOMAR, 2006). The sample is stratified by age, gender, education, federal state, household size, location indicator, and household net income. Due to the nature of the sampling procedure, no take-up rates are available.

[6]Inconsistent individuals were excluded from the sample, though it did not change the results.

Due to the very low numbers, the unemployed and the working poor are jointly addressed by the variable *Receives transfers*.[7]

The descriptive statistics reveal that about 26 percent of the sample is retirees. The overall health status is 2.25—that is, slightly better than average; somewhere between good and OK. Twenty-eight percent of subjects receive child benefits, which are not means tested. In contrast, 9 percent receive transfers that are means tested and thus relate to a large extent to the unemployed or the working poor.[8] In the subsequent analysis, these observable socio-demographic characteristics are used as explanatory class membership variables regarding preferences for redistribution in the latent class models.[9]

5. Results

5.1. *Model Selection*

Before turning to the interpretation of our results, we assess the appropriateness of different models. We run a multinomial logit (MNL) model, an error component logit (ECL) model, a random parameter logit (RPL) model, and a latent class (LC) model. We use AIC, AIC3, CAIC, and BIC as selection criteria for the best fitting model. The criteria differ in the way additional parameters are penalized. While all criteria are based on the log-likelihood function, an additional term is added to control for overfitting (Dziak *et al.*, 2012).[10] While AIC and AIC3 work well for small sample sizes, there is a general tendency to overfit by favoring a model with too many parameters. For a large number of observations, BIC and CAIC perform better in selecting the "best" model by using penalty functions for the number of parameters. However, according to Bhat (1997), these two measures risk to underfit the model. Thus there is no objective measure to pick one best criterion. In addition to statistical criteria, meaningfulness of results as a second dimension needs to be considered (Dziak *et al.*, 2012).

Table A.4 in the appendix reports the statistics of the different models. (See figure A.1 in the appendix for a graphical illustration.) Log-likelihood values (LL) and the selection criteria are decreasing from the MNL to the RPL model, suggesting the latter to be the best within the group of mixed

[7]While this selection obviously plays along the self-interest argument, we are fully aware that this low number of variables cannot fully control all potentially relevant aspects, leaving even aside complex aspects like expectations about future developments, etc. However, this setup allows for a clear identification of relationships and is sufficient to highlight the relevance of accounting for latent and potentially discretely distributed factors.

[8]In our sample, only seven retirees receive social welfare, so the overlap between *Retired* and *Receives transfers* is negligible.

[9]We do not account for any nationality variables for explaining class membership, as the sample consists of Germans who are eligible to vote. By law, foreigners do not have this right. However, there are 2.5 percent foreigners in our dataset. Stratified by individuals from Western Europe (0.65 percent) and other countries (1.75 percent), the number of observations is too small to be included in an empirical analysis. Additionally, only 2.5 percent of the sample do have a migration background.

[10]AIC3 (Bozdogan AIC) is $(-2LL+3P)$; AIC (Akaike Information Criterion) is $(-2LL+2P)$; BIC (Bayesian Information Criterion) is $(-2LL+P[\log(N)])$; CAIC (Consistent AIC) is $(-2LL+P[\log(N)+1])$.

logit models with continuous distributions.[11] Examining the LC models with two to 10 classes, the LL values decrease, as expected, as more classes are added, since more heterogeneity of the data is explained. By definition, the LL decreases even further, the more classes are added. AIC and AIC3 also decrease continuously with each class that is added. Thus LL, AIC, and AIC3 suggest using the LC10 model. However, for the LC model, BIC and CAIC point to the LC3 model as the best with regard to goodness-of-fit.

Examining the three potential models (RPL, LC3 and LC10) in more detail reveals that LC10 exhibits seven classes with very small class probabilities (≤ 10 percent).[12] Generally, the more classes added, the more fractionalized the classes are, and the larger becomes the proportion of classes with large standard errors and enormous confidence intervals, which impedes a meaningful interpretation of the results. This comports with the problems associated with AIC and AIC3 as selection criteria of overfitting the model. Accordingly, we end up with a choice between the RPL and LC3 model. While some of the selection criteria favor the first model, others favor the second, including overall improvements in the LL values and the pseudo R^2. AIC and AIC3 would suggest the LC3 model, while CAIC and BIC favor the RPL model. Thus since there is a slight tendency for the RPL model to perform best according to our criteria, but the LC model conveys some additional information as well as relaxing distributional assumptions regarding the heterogeneity, both models will be discussed consecutively below.

5.2. *MNL, ECL, and RPL*

Table 1 shows the results of the MNL, the ECL and the RPL models. In all of them, the main effects of the program attributes are significant, as are the standard deviations of the program attributes in the RPL model. A comparison of the three shows no differences in signs across attributes or with respect to the internal ranking of the attributes.

The results suggest that people in general oppose a tax increase but would like a larger budget for redistribution. Delving into whom this money should be given to, respondents on average prefer to redistribute more to retirees and families with children versus people who are sick or in need of care (our base level). In contrast, respondents prefer to decrease the redistribution to unemployed and low-income individuals versus sick and those in need of care. In addition, they prefer to redistribute to Germans versus people coming from both within and beyond the western part of Europe, respectively. Finally, the positive and significant estimate of the ASC shows a strong preference for the status quo, all else equal.

The MWTP for an expansion of redistribution is somewhere between 0.42 for the RPL[13] model and 0.5 for MNL and ECL, suggesting that individuals on average

[11]Note that the LC model is not nested in the RPL model, thus a likelihood ratio test between the two is not appropriate.

[12]Results can be obtained from the authors upon request. We also examined the results of LC4 to LC9 but decided to stick with LC3 and LC10 for the sake of simplicity. None of the other LC model configurations produced results that were clearly superior.

[13]For statistical reasons for RPL the MWTP should not be calculated, as this implies the division of two normal distributions. In such a ratio distribution, moments do not exist (Hole, 2008; Hole and Kolstad, 2012).

TABLE 1

Error component and random parameter logit model results

	[1]		[2]		[3]	
	MNL		ECL		RPL	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Tax	−0.086***	(0.003)	−0.093***	(0.003)	−0.152***	(0.008)
Redistribution	0.043***	(0.003)	0.046***	(0.003)	0.064***	(0.006)
Beneficiaries (base sick and persons in need of care)						
Retirees	0.028***	(0.006)	0.030***	(0.006)	0.061***	(0.010)
Families	0.027***	(0.007)	0.028***	(0.007)	0.039***	(0.011)
Unemployed	−0.032***	(0.007)	−0.035***	(0.007)	−0.058***	(0.011)
Working Poor	−0.039***	(0.011)	−0.042***	(0.011)	−0.070***	(0.018)
Nationality of recipients (base German)						
West Europe	−0.065***	(0.009)	−0.072***	(0.009)	−0.131***	(0.016)
Others	−0.055***	(0.005)	−0.059***	(0.006)	−0.089***	(0.009)
ASC	0.507***	(0.038)	0.549***	(0.043)	0.791***	(0.064)
Standard Deviation of random parameters						
Tax					0.112***	(0.009)
Redistribution					0.094***	(0.009)
Beneficiaries (base sick persons and persons in need of care)						
Retirees					0.146***	(0.012)
Families					0.144***	(0.015)
Unemployed					0.118***	(0.018)
Working Poor					0.122***	(0.033)
Nationality of Recipients (base German)						
West Europe					0.185***	(0.028)
Others					0.135***	(0.019)
EC			0.644***	(0.038)	0.959***	(0.067)
Number of Obs.	10654		10654		10654	
Number of Resp.	1522		1522		1522	
LL	−6391.672		−6323.172		−6115.995	
Adj. Rho squared	0.078		0.144		0.172	
# Parameters	9		10		18	
AIC	12801.344		12666.345		12267.990	
AIC3	12810.344		12676.345		12285.990	
CAIC	12875.807		12749.082		12416.916	
BIC	12866.807		12739.082		12398.916	

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

are willing to pay 0.42 (0.5) percentage points of income for an additional percentage point of GDP devoted to redistribution beyond the status quo. Looking at the amount they are willing to contribute and the amount that should be redistributed a small gap of less than one billion Euros per year remains. On first glance, this seems irrational, but one has to bear in mind that other expenses (e.g. for environmental issues, infrastructure, etc.) could be cut or other sources of taxation besides personal tax and social insurance contributions (e.g. business taxes) could be used to close this gap. The magnitude and rank order of MWTP values are very similar across models.

Finally, when examining the heterogeneity in the samples (i.e. the standard deviations), the results of the RPL model show that a large degree of heterogeneity is observed across all attributes. This suggests that many of the respondents have either substantially weaker or stronger preferences than the estimated mean. This heterogeneity may likely stem from heterogeneous appreciation of the different attributes, e.g. some individuals feeling a stronger urge to support families with children than others. The RPL model is adequate to capture this heterogeneity as long as the distributional assumptions are met. There is some flexibility to the kind of distribution being applied, but basically all of them being unimodal.[14] In our case, we chose the most commonly used normal distribution. This distributional assumption implies that the highest probability for a parameter is at its mean. For preferences toward the support of families with children this would imply that while some prefer higher or lower values, the majority still gathers around the mean. It could though be misleading using a continuous distribution if the preferences in the population were spiked—e.g. many of the respondents have either substantially weaker or stronger preferences than the estimated mean—then one would still reach the same conclusion, though this time being the wrong one.

As mentioned, we find a large degree of heterogeneity in the RPL model. This unobserved heterogeneity is per definition continuously distributed following a normal distribution. This suggests that many of the respondents have either substantially weaker or stronger preferences than the estimated mean. Combined with the somewhat ambiguous test statistics from above, this might suggest that the sample could be highly segmented. If this goes along for example with a bimodal (or multi-modal) distribution, the highest probability for a parameter is very unlikely at its mean. In such a case, RPL would struggle heavily to accurately capture these kind of preferences.

5.3. *Latent Class Model*

The latent class model accounts for both, observable characteristics and unobserved heterogeneity. In contrast to the RPL model, heterogeneity in the LC model is modeled as a discrete variation instead of a continuous variation (results are presented in Table 2). In all the three classes in the LC model, the coefficients for Tax and Redistribution have the same signs as in the preceding models. Between classes, the internal ranking of the attributes varies, and signs change. Furthermore, not all attributes are significant in all classes. This much-differentiated picture suggests that the assumption of a continuous distribution across the full sample is at least questionable.

The class-membership variables indicate that retirees are less likely to be in classes 1 and 2, with the latter being also characterized by healthier persons compared to the other two classes. Contrary to the retirees, individuals receiving child benefits are more likely to be part of class 1 and 2. Class 1 has also a significantly higher proportion of transfer recipients. The average class probability indicates the size of the classes. Class 1 represents 30.6 percent, class 2 23.0 percent and class 3 46.5 percent of the individuals in our sample.

[14]One can also apply a uniform distribution (Train 2009), which however would not solve the problems of the RPL with multi-modal distributions.

TABLE 2

LATENT CLASS MODEL WITH THREE CLASSES

	Class 1		Class 2		Class 3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Tax	−0.040***	(0.008)	−0.366***	(0.033)	−0.071***	(0.007)
Redistribution	0.032***	(0.008)	0.057***	(0.012)	0.058***	(0.008)
Beneficiaries (base sick and persons in need of care)						
Retirees	−0.045***	(0.014)	0.049**	(0.022)	0.116***	(0.018)
Families	0.052***	(0.016)	0.051**	(0.024)	0.009	(0.017)
Unemployed	−0.029*	(0.016)	−0.038	(0.029)	−0.017	(0.014)
Working Poor	−0.049**	(0.024)	0.004	(0.043)	−0.041*	(0.022)
Nationality of recipients (base German)						
West Europeans	0.006	(0.021)	−0.158***	(0.033)	−0.105***	(0.020)
Other	−0.022	(0.014)	−0.048**	(0.023)	−0.119***	(0.014)
ASC	0.487***	(0.108)	−0.082	(0.143)	0.931***	(0.084)
Class membership variables						
Retireed	−1.15***	(0.272)	−1.955***	(0.323)		
Self-assessed health	−0.21	(0.144)	−0.266**	(0.123)		
Receives child benefits	0.76***	(0.233)	0.408*	(0.211)		
Receives transfers	0.81**	(0.343)	−0.037	(0.363)		
Constant	0.07	(0.354)	0.214	(0.289)		
Avg. class prob.	0.306		0.230		0.465	
Number of Obs.	10654					
Number of Resp.	1522					
LL	−6042.968					
Adj. Rho squared	0.182					
# Parameters	37					
AIC	12160					
AIC3	12197					
CAIC	12466					
BIC	12429					

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

For a meaningful comparison between the classes, we have to turn to the marginal willingness-to-pay (MWTP) estimates due to the scaling issue mentioned earlier (Table 3). While positive in all classes, we see that members of class 2 have a considerably lower MWTP for an expansion of the overall redistributive budget. (This MWTP is defined as the willingness to cede a certain number of percentage points of income for an additional percentage point of GDP devoted to redistribution beyond the status quo.) Generally, an expansion of the redistributive budget may increase the amount of money received by certain beneficiaries even if their share remains stable or perhaps even moderately shrinks.

In class 1, families with kids as well as the sick (the reference category) benefit from an expansion of their share at the expense of the other three beneficiary groups, that is, retirees, the unemployed, and working poor. At the same time, there is no particular preference for a change regarding the allocation between recipients according to their nationality. The high ASC implies that members of this group have a rather strong preference for the status quo, all else equal. A possible explanation is that, for such individuals, any change deviating from the status quo is disturbing and brings uncertainty, resulting in a disutility that needs to be compensated.

TABLE 3

Mean and variance of marginal willingness-to-pay values for the three-class model

	Class 1		Class 2		Class 3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Redistribution	0.797***	(0.177)	0.155***	(0.029)	0.816***	(0.090)
Beneficiaries (bas sick and persons in need of care)						
Retirees	−1.120**	(0.439)	0.134**	(0.057)	1.640***	(0.270)
Families	1.289***	(0.484)	0.139**	(0.066)	0.127	(0.236)
Unemployed	−0.714*	(0.407)	−0.103	(0.082)	−0.247	(0.203)
Working Poor	−1.216*	(0.662)	0.011	(0.116)	−0.583*	(0.316)
Nationality of recipients (base German)						
West Europeans	0.158	(0.530)	−0.433***	(0.095)	−1.487***	(0.298)
Other	−0.557	(0.358)	−0.131**	(0.064)	−1.686***	(0.230)
ASC	12.181***	(3.438)	−0.224	(0.392)	13.185***	(1.679)

Note: The variance of WTP was calculated using the Delta-method (Greene, 2008).
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Class 2 is clearly distinct from class 1. In this class, the MWTP for giving more resources to the retirees is small but positive. Families with kids are also favored. The members of class 2 prefer an increase of the shares dedicated to retirees and families. This is a somewhat surprising combination, but at 23 percent, this class is substantial. As there are no significant results for unemployed and working poor, the positive MWTP for the first two beneficiary groups goes along with a negative one for the sick. Regarding the nationality of recipients, both coefficients for foreigners are negative. The ASC is not significant, meaning that this group—despite comparatively modest absolute values of its MWTP estimates—is very likely to opt for an alternative redistributive scenario that fits with its preferences regarding the aforementioned attributes.

The last class exhibits a positive—and compared to class 2—much higher positive MWTP in favor of the retirees. This goes on the expense of working poor and of the sick. The coefficients for recipients of child benefits and the unemployed are not significant, whereas there is a strong negative MWTP for foreign nationalities. Similar to class 1, the ASC is very high, indicating a strong preference for the status quo.

5.4. *Comparing Random Parameter Logit and Latent Class Models*

When comparing the RPL and the LC models, we see that the magnitude of the MWTP values is comparable. However, we also see that the former model averages out considerable discrepancies that become apparent in the LC model. This goes beyond pure differences in the magnitudes in MWTP. We also see changes in signs, especially when looking at retirees, recipients of child benefits, and the sick. While the RPL model suggests that there is an overall preference for expanding the share for retirees, the LC model reveals that there is a group of 30.6 percent in the population that has a significantly negative MWTP in this respect. This is a sizeable share that would likely play an important role in any political deliberation.

As in this case, the statistical criteria alone are not sufficient to identify the appropriate model; the meaningfulness of results also needs to be considered (Dziak *et al.*, 2012). We argue that our results clearly show that, besides a better fit (on the expense of 19 additional parameters), the LC model conveys more detail about the underlying preference structures of the German population as heterogeneity is not only incorporated by unobserved but also by observable factors. Looking only at the RPL results could be misleading.

5.5. *Relating class membership variables to marginal-willingness-to-pay estimates*

Linking the class membership variables to the class specific MWTP estimates, we see that in eight out of 12 cases (three classes with four class membership variables each) the relationship is plausible. For example, nonretired individuals have a much higher probability to be part of class 1, which in turn favors a reduction of the share dedicated to the retirees. In class 3, we see the opposite scenario: retirees favoring an expansion of their share of the redistributive budget. Across all classes, we also see a very plausible pattern for individuals who receive child benefits and the accompanying MWTP estimates.

It is tempting to say class 3 is the "retiree class" and that retirees favor an expansion of the their share, while younger individuals prefer to cut the retirees' allotment. Looking at the class membership variables, this stance seems to be supported. But the descriptive statistics reveal that other unobserved factors must also play an important role. While 81 percent of all retirees are in class 3, retirees account for only 45 percent of members of the class. What is more, 36 percent of all non-retired individuals are most likely members of class 3. This implies that they fit best in a class that favors a considerable reallocation of the redistributive budget in favor of retirees. The age structure of the non-retired members of the three classes reveals that this may be very likely due to a higher share of individuals who are closer to the retirement age in class 3 (46 years) than in in classes 1 (41 years) and 2 (42 years), respectively. This would support self-interest-based hypotheses for the explanation of redistributive preferences.

Looking at individuals who receive child benefits, the class membership variables display a plausible pattern with regard to the MWTP estimates. We also see that they are primarily present in classes 1 (38 percent) and 2 (34 percent), though with 28 percent there is also a significant share of child-benefits recipients in class 3. Considering that there are extensive family benefits in Germany, it does not seem to be very surprising that at least a part of the concerned population does not want a change of the status quo.

The descriptive statistics of the classes may also help to at least partially explain the four instances in which the results of class-membership variables are surprising when relating them to the MWTP estimates. Looking, for example, at class 1, we see that transfer recipients are much more likely to be part of this class, while at the same time the MWTP for the unemployed and the working poor is negative. However, this is plausible, if we see that, despite of 49 percent of all transfer recipients being most likely part of class 1, this group constitutes just about 17 percent of the members of this class. Looking at the paradox regarding healthier individuals in class 1 requesting more benefits for the sick one might argue that the high share of recipients of child benefits plays into that, as children receive social health insurance free of charge. Another explanation for this result could be other-regarding behavior—such as altruism or inequality aversion—healthy people wanting to help the sick. A factor that may help to explain the converse situation in class 3 (sicker individuals giving away benefits for the sick in favor of retirees) may be that the elderly are happy with their healthcare coverage—happier than younger people with less exposure to the healthcare system. However, these aspects warrant further analysis, which is beyond the scope of this paper.

6. Discussion

The first aim of this paper is to highlight the relevance of observed and unobserved heterogeneity in a public economics topic, namely, preferences for redistribution. Our results clearly show that both observed as well as unobserved heterogeneity do have a significant impact on the results. Examining the statistical criteria, there is little difference between the RPL model and the preferred LC3 model; CAIC and BIC point toward the first model, while AIC and AIC3 point toward the latter. However, the LC model conveys much more information on the structure of subgroups in the population. Moreover, it relaxes the assumptions regarding a continuous factor variation. Even without any class membership variables, it opens the possibility for an explorative analysis of the results. To illustrate this, we have run a model assuming that all heterogeneity is latent by estimating an additional 3 class model without any class-specific variables except a constant. The overall results resemble the ones presented in the preceding tables including class membership variables. (See Table A.5 in the appendix.) The signs of the coefficients are identical, and the magnitude of the effects has the same pattern. Just two variables (*other* in class two and *working poor* in class three) that were significant at the 5 and 10 percent levels, respectively, are not significant anymore, and the class sizes change moderately. Thus overall the interpretation of the results does not change considerably. The LL is −6113, that is, three units better than in the RPL model but 70 units worse than the LC3 model, including the class membership variables. When accounting for the number of parameters the model is clearly outperformed by both RPL and LC3 with class membership variables, no matter which criterion is used. Nonetheless, even when no observables are available as class membership variables, the results of the LC3 model give a much clearer picture of the heterogeneity of preference structures.

This is valuable whenever heterogeneity in a population needs to be understood. In our case, as illustrated above, even without class membership variables, we see clear differences in preference structures between the classes and get an idea of the size of the different subgroups. If some observable class membership variables are available, one can test the extent to which these variables are sufficient to identify class membership or whether other unobservable factors matter for class composition. With regard to this identification of subgroups, our results may also provide valuable insights for future research that uses such an approach in the analysis of interest groups. Research on the relation between interest groups and redistribution underlines the need for further differentiation beyond observable characteristics (e.g. Plotnick, 1986; Kristov *et al.*, 1992).[15]

Besides practical issues such as the computational power required for the estimation of the LC models, one has to bear in mind that it is difficult to establish objective measures for the identification of the "true" model. In many cases, including ours, you must account for the meaningfulness of results and cannot solely rely on statistical measures. Furthermore, the computational burden increases drastically, the more variables added and the more classes specified. Thus we see the strength of this approach in an application for (explorative) analysis of data in which both observed and unobserved heterogeneity are likely to play an important role. While this is already successfully implemented in areas such as health economics—also in combination with DCEs (Mentzakis *et al.*, 2011)— to the best of our knowledge, there are no applications so far in public or political economics.

Regarding the aim to contribute to the general literature on income redistribution, our paper is unique in that it combines a DCE with an explicit analysis of observed as well as unobserved heterogeneity. Based on a dataset that is representative for the German voting-age population, we find considerable heterogeneity in preferences for redistribution. While the overall result—Germans tend to favor an extension of the redistributive system—comports with the literature (Pfarr, 2013), applying the LC model we can identify three clearly distinct subgroups, all favoring redistribution but with diverse preferences regarding the respective target groups. While most observable characteristics used to explain class membership are plausible, the results also show that there are groups of individuals who are members of less plausible classes, that is, that observables can explain only a part of the variation. Omitting unobserved heterogeneity and even enforcing the assumption of continuous factor variation increases the risk that the estimated results are not meaningful as they average out considerable discrepancies.

In our setup, we chose class membership variables assuming self-interested motives. It is well known that many more factors, such as fairness, altruism, and other aspects discussed in behavioral economics, play an important role. However, these factors are difficult to capture and are thus, in many instances, not available to researchers. In such cases, most prior studies account for observable controls and, to some extent, for unobservable heterogeneity, for example, by applying RPL models. In these instances, the impact of potential unobservable factors is not visible. Irrespective of the type of data used, the LC model allows us to see how strong the population is segmented beyond observable characteristics, thereby avoiding potential bias if

[15]One might consider labeling the subgroups that we identify latent interest groups. Building on the conceptualizations of Truman (1951) and Olson (1965), any collection of individuals and ultimately voters that share common characteristics, attitudes or interests can form an interest group. As long as this group lacks any form of organization and interaction, this is called a potential or a *latent interest group.*

the underlying distribution is discontinuous. With respect to our findings, some of the less plausible class variables mentioned above could be caused by such behavior—for example, healthy persons exhibiting altruism toward the less healthy, etc. A central element of concern within the framework of other-regarding preferences or social preferences is also if individuals exhibit inequality aversion as proposed by Fehr and Schmidt (1999). Again – this is not captured in our models in any other way than as potential reasons for non-plausible results as described above. We do acknowledge that other-regarding preferences could play an important role in individuals' preferences for redistribution, but given the potential caveats in capturing these we have disregarded these in our econometric specification. One potential link between observable characteristics and other-regarding preferences is observed by Carpenter *et al*. (2005) as well as List (2004). They both find that the tendency to exhibit other-regarding preference behavior increases with age. Looking at our results, this seems not to be the case, as the majority of the older part of the sample is in class 3, who favor of an expansion of their own share. Unfortunately, as argue before, any such behavior remains speculative in our case.

One should also consider that an overall expansion of the redistributive budget may increase the amount of money received by certain recipients even if the share dedicated to these respective groups remained stable or perhaps even moderately diminished. To account for this aspect, we also tested a model that included a variable that equals one if an individual believed that he or she would be a net beneficiary from increased levels of income redistribution and zero otherwise. The results regarding all other variables remain unchanged. (See tables A.6 and A.7 in the appendix.) The class membership variable itself was highly significant for increasing the probability of being member in class 2. This seems very plausible in relation to the high willingness to opt for alternative scenarios in contrast to the other groups. One caveat concerning this could be caused by the hypothetical nature of the DCE approach—in terms of hypothetical bias. In contrast to e.g. lab experiments, DCEs in the field rarely include real incentives, which could generate inflated WTP values. Research has though shown that the internal ranking of characteristics is not affected by the hypothetical nature of the instrument, whereas no clear-cut conclusions exist with regards to the absolute values—Carlsson and Martinsson (2001) and Mørkbak *et al*. (2014) find no differences in WTP, whereas Johansson-Stenman and Svedsäter (2008); Ready *et al*. (2010); Taylor *et al*. (2010) and Grebitus *et al*. (2013); all find differences between hypothetical and incentivized WTP estimates; Cameron *et al*. (2002) and List *et al*. (2006) only show very small differences. For a more thorough overview of these studies, see e.g. Ready *et al*. (2010). From a behavioral point of view, implications are the same, whether experiments are incentivized or not (Camerer and Hogarth, 1999, Ashraf *et al*., 2006).

From a policy perspective, these results are interesting, as they can indicate the extent to which reforms favoring certain groups might also find support outside of such groups. Even without necessarily having an observable identifier, they can approximate the extent to which people will support certain reform proposals. Typically, standard agreement questions have been used for this purpose, with the risk of introducing "yeah-saying" and with no budgetary constraints and trade-offs (Corneo and Grüner, 2000; Alesina and La Ferrara, 2005). A consequence of using such methods is that attitudes rather than preferences are elicited (Eagly and Chaiken, 1996; Kahneman *et al*., 1999). The advantage of the DCE setup is that it avoids these issues. Of course DCE does not secure perfect compatibility, but it makes it more compatible since it is less straight forward for respondents to act strategically, and moreover it directly forces respondents' to make trade-offs between attributes. In the present survey we have made the scenario as realistic as possible, with the aim of increasing consequentialism to secure compatibility (Vossler *et al*., 2012). Thus we argue that these results are more reliable from a policy perspective than standard agreement questions and are furthermore consistent with microeconomic theory.

7. Conclusion

Prior studies have shown that certain observables help to explain preferences for redistribution while acknowledging that there is also latent heterogeneity. However, the implications of this heterogeneity remained largely unclear. Our results show that latent and potentially discontinuously distributed factors can heavily impact on the interpretation of the findings. For example, while we find a significant difference in preferences between retirees and non-retirees, we see that there is a considerable group of non-retirees who share preferences with retirees. When analyzing, for example, the role of self-interest with regard to preferences for redistribution, this needs to be accounted for, a task that a RPL model alone cannot achieve.

Overall, our results based on the RPL model show that people in general are against a tax increase, as expected, but that they would like a larger budget for redistribution. Moreover, the RPL results show that respondents on average prefer to redistribute more to retirees and families with children versus people who are sick or in need of care (our base level). In contrast, respondents prefer to decrease the redistribution to unemployed and low-income individuals versus sick and those in need of care. In addition, they prefer to redistribute to Germans versus people coming from both within and beyond the western part of Europe, respectively. Finally, the RPL model shows a large degree of heterogeneity. Examining the structure of this heterogeneity through a LC model, we identified three clearly distinct subgroups. All of them prefer a higher level of redistribution but differ regarding the allocation of the redistributive budget. Finally, our results also show that a vast majority of the population is very reluctant to deviate from the status quo, even when favoring a particular change in the redistributive system. Thus additional measures would be needed to persuade them to change.

Summarizing, we argue that our approach—accounting for both observed and unobserved heterogeneity in the deterministic part of the utility function—is a considerable step forward that may point the way for further research. The LC model is independent of the data used; it may or may not be combined with a

DCE. Irrespective of the data-generating process, a researcher can determine groups that share common preferences or attitudes and estimate their size while controlling for unobservable factors. This goes well beyond the commonly applied models.

References

Alesina, A. and G.-M. Angeletos, "Fairness and Redistribution," *American Economic Review*, 95, 960–80, 2005.

Alesina, A., G. Cozzi, and N. Mantovan. "The Evolution of Ideology, Fairness and Redistribution," *Economic Journal*, 122, 1244–61, 2012.

Alesina, A. and P. Giuliano, "Preferences for Redistribution," in J. Benhabib, M.O. Jackson and A. Bisin, eds., *Handbook of Social Economics*, 1A, 93–132, North Holland, Amsterdam, 2011.

Alesina, A. and E. Glaeser, *Fighting Poverty in the US and Europe: A World of Difference*, Oxford University Press, Oxford, 2004.

Alesina, A. and E. La Ferrara, "Preferences for Redistribution in the Land of Opportunities," *Journal of Public Economics*, 89, 897–931, 2005.

Alesina, A. and D. Rodrik, "Distributive Politics and Economic Growth," *Journal of Economics*, 109, 465–90, 1994.

Andreoni, J. and J. Miller, "Giving According to GARP: An Experimental Test of the Consistency of Preferences for Altruism," *Econometrica*, 70, 737–52, 2002.

Ashraf, N., D. Karlan, and W. Yin, "Tying Odysseus to the Mast. Evidence From a Commitment Savings Product in the Philippines," *Quarterly Journal of Economics*, 121, 635–72, 2006.

Bateman, I. J., R. T. Carson, B. Day, M. Hanemann, and N. Hanley, *Economic Valuation with Stated Preference Techniques*, Elgar, Cheltenham, 2002.

Bech, M., T. Kjær, and J. Lauridsen. "Does the Number of Choice Sets Matter? Results from a Web Survey Applying a Discrete Choice Experiment," *Health Economics*, 20, 273–86, 2011.

Benabou, R. and J. Tirole, "Belief in a Just World and Redistributive Politics," *Quarterly Journal of Economics*, 121, 699–746, 2006.

BMAS, Lebenslagen in Deutschland, Der 3. Armuts- und Reichtumsbericht der Bundesregierung, Berlin, 2008.

Boeri, T., A. -H. Börsch-Supan, and G. Tabellini, "Would You Like to Shrink the Welfare State? A Survey of European Citizens," *Economic Policy*, 16, 7–50, 2001.

———, "Pension Reforms and the Opinions of European Citizens," *American Economic Review*, 92, 396–401, 2002.

Bolton, G. E. and A. Ockenfels, "ERC. A Theory of Equity, Reciprocity, and Competition," *American Economic Review*, 90, 166–93, 2000.

Boxall, P. C. and W. L. Adamowicz, "Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach," *Environmental and Resource Economics*, 23, 421–46, 2002.

Brownstone, D. and K. Train, "Forecasting New Product Penetration with Flexible Substitution Patterns," *Journal of Econometrics*, 89, 109–29, 1998.

Camerer, C. F and R. M. Hogarth, "The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework," *Journal of Risk and Uncertainty*, 19, 7–42, 1999.

Cameron, T. A., G. L. Poe, R. G. Ethier, and W. D. Schulze, "Alternative Non-market Value-Elicitation Methods. Are the Underlying Preferences the Same?," *Journal of Environmental Economics and Management*, 44, 391–425, 2002.

Carlsson, F. and P. Martinsson., "Do Hypothetical and Actual Marginal Willingness to Pay Differ in Choice Experiments?," *Journal of Environmental Economics and Management*, 41, 179–92, 2001.

Carpenter, J. P., S. Burks, and E. Verhoogen, "Comparing Students to Workers: The Effects of Social Framing on Behavior in Distribution Games," in G.W. Harrison, J. P. Carpenter and J. A. List, eds., *Field Experiments in Economics, Research in Experimental Economics*, 10, 261–89, Emerald, Bingley, 2005.

Charness, G. and M. Rabin, "Understanding Social Preferences with Simple Tests," *Quarterly Journal of Economics*, 117, 817–69, 2002.

Cooper, D. J. and J. H. Kagel, "Other-Regarding Preferences: A selective Survey of Experimental Results," in J. H. Kagel and A. E., eds., *Handbook of Experimental Economics*, Princeton University Press, Princeton, 2013.

Corneo, G. and H. P. Grüner. “Social Limits to Redistribution,” *American Economic Review*, 90, 1491–507, 2000.
Durante, R., L. Putterman, and J. van der Weele, “Preferences for Redistribution and Perception of Fairness. An Experimental Study,” *Journal of the European Economic Association*, 12, 1059–86, 2014.
Dziak, J., D. L. Coffman, S. T. Lanza, and L. Runze, “Sensitivity and Specificity of Information Criteria,” Technical Report Series, Pennsylvania State University, 2012.
Eagly, A. and S. Chaiken, “Attitude Structure and Function,” in D. Gilbert, S. Fiske and G. Lindzey, eds., *Handbook of Social Psychology*, 269–322, McGraw-Hill Book Co., New York, 1996.
ESOMAR, ESOMAR/WAPOR Guide to Opinion Polls and Published Surveys, Amsterdam, 2006.
Fehr, E. and K. M. Schmidt, “A Theory of Fairness, Competition, and Cooperation,” *Quarterly Journal of Economics*, 114, 817–68, 1999.
Feld, L. P., J. A. V. Fischer, and G. Kirchgässner, “The Effect of Direct Democracy on Income Redistribution: Evidence for Switzerland,” *Economic Inquiry*, 48, 817–40, 2010.
Fields, G. and E. Ok, “Measuring Movement of Incomes,” *Economica*, 66, 455–71, 1999.
Foley, M. W. and B. Edwards, “The Paradox of Civil Society,” *Journal of Democracy*, 7, 38–52, 1996.
Fong, C, “Social Preferences, Self-Interest, and the Demand for Redistribution,” *Journal of Public Economics*, 82, 225–46, 2001.
———, “Prospective Mobility, Fairness, and the Demand for Redistribution,” Working Paper, Carnegie Mellon University, 2006.
Fong, C. M., S. Bowles, and H. Gintis, “Strong Reciprocity and the Welfare State,” in S.-C. Kolm and J. M. Ythier, eds., *Handbook of the Economics of Giving, Altruism and Reciprocity, Handbook in Economics*, 23, 1439–64, North Holland, Amsterdam, 2006.
Fong, C. M. and F. Oberholzer-Gee, “Truth in Giving: Experimental Evidence on the Welfare Effects of Informed Giving to the Poor,” *Journal of Public Economics*, 95, 436–44, 2011.
García-Valiñas, M. A., R. F. Llera, and T. Benno, “More Income Equality or Not? An Empirical Analysis of Individuals’ Preferences for Redistribution,” Working/Discussion Paper, School of Economics and Finance, University of Oviedo, 2008.
Gravelle, H. and R. Rees, *Microeconomics*, 3rd ed, Prentice Hall Financial Times, Harlow, England, New York, 2004.
Grebitus, C., J. L. Lusk, and R. M. Nayga, “Explaining Differences in Real and Hypothetical Experimental Auctions and Choice Experiments with Personality,” *Journal of Economic Psychology*, 36, 11–26, 2013.
Greene, W. H., *Econometric analysis*, 6th ed., Pearson Prentice Hall, Upper Saddle River, NJ, 2008.
Gruber, J. and D. M. Hungerman, “Faith-Based Charity and Crowd-Out During the Great Depression,” *Journal of Public Economics*, 91, 1043–69, 2007.
Guillaud, E, “Preferences for Redistribution: An Empirical Analysis over 33 Countries,” *Journal of Economic Inequality*, 11, 57–78, 2013.
Hayo, B. and F. Neumeier, “Public Preferences for Government Spending Priorities: Survey Evidence from Germany,” Joint Discussion Paper Series in Economics, 2014.
Hensher, D. A., J. M. Rose, and W. H. Greene, *Applied Choice Analysis*, Cambridge University Press, Cambridge, 2015.
Hensher, D. A. and W. H. Greene, “The Mixed Logit model: The state of practice,” *Transportation*, 30, 133–76, 2003.
Herriges, J. A. and D. J. Phaneuf, “Inducing Patterns of Correlation and Substitution in Repeated Logit Models of Recreation Demand,” *American Journal of Agricultural Economics*, 84, 1076–90, 2002.
Hess, S., M. Bierlaire, and J. W. Polak, “A Systematic Comparison of Continous and Discrete Mixture Models,” *European Transport*, 37, 35–61, 2007.
Hole, A. R., “Modelling Heterogeneity in Patients’ Preferences for the Attributes of a General Practitioner Appointment,” *Journal of Health Economics*, 27, 1078–94, 2008.
Hole, A. R. and J. Riise Kolstad, “Mixed Logit Estimation of Willingness to Pay Distributions: A Comparison of Models in Preference and WTP Space using data from a Health-Related Choice Experiment,” *Empirical Economics*, 42, 445–69, 2012.
Johansson-Stenman, O. and H. Svedsäter, “Measuring Hypothetical Bias in Choice Experiments. The Importance of Cognitive Consistency,” *B. E. Journal of Economic Analysis & Policy*, 8, 2008.
Kahneman, D., I. Ritov, and D. Schkade, “Economic Preferences or Attitude Expression? An Analysis of Dollar Responses to Public Issues,” *Journal of Risk and Uncertainty*, 19, 203–35, 1999.
Kanninen, B. J., “Optimal Design for Multinomial Choice Experiments,” *Journal of Marketing Research*, 39, 214–27, 2002.
Karabarbounis, L., “One Dollar, One Vote,” *Economic Journal*, 121, 621–51, 2011.

Kristov, L., P. Lindert, and R. McClelland, "Pressure Groups and Redistribution," *Journal of Public Economics*, 48, 135–63, 1992.
Kuhfeld, W. F., "Construction of Efficient Designs for Discrete-Choice-Experiments," in R. Grover and M. Vriens, eds., *Handbook of Marketing Research*, 312–63, Sage Publ., Thousand Oaks, 2006.
Kuhfeld, W. F., R. D. Tobias, and M. Garratt, "Efficient Experimental Design with Marketing Research Applications," *Journal of Marketing Research*, XXXI, 545–57, 1994.
Lancaster, K. J., "A New Approach to Consumer Theory," *Journal of Political Economy*, 74, 132–57, 1966.
List, J. A., "Young, Selfish and Male: Field Evidence of Social Preferences," *Economic Journal*, 114, 121–49, 2004.
List, J. A., P. Sinha, and M. H. Taylor, "Using Choice Experiments to Value Non-Market Goods and Services. Evidence from Field Experiments," *Advances in Economic Analysis & Policy*, 5, 1–37, 2006.
Louviere, J. J., D. A. Hensher, and J. D. Swait, *Stated Choice Methods: Analysis and Application*, Cambridge Univ. Press, Cambridge, 2000.
Louviere, J. J. and E. Lancscar, "Choice Experiments in Health: The Good, the Bad, the Ugly and Toward a Brighter Future," *Health Economics, Policy and Law*, 4, 527–46, 2009.
Luce, R. D., *Individual Choice Behavior*, Greenwood Press, Westport, CO, 1959.
Luttmer, E. F. P. and M. Singhal, "Culture, Context, and the Taste for Redistribution," *American Economic Journal: Economic Policy*, 3, 157–79, 2011.
McFadden, D., "Conditional Logit Analysis of Quantitative Choice Behavior," in P. Zarembka, ed., *Frontiers in econometrics*, 105–42, Academic Press, New York, 1974.
———, "Economic Choices," *American Economic Review*, 91, 351–78, 2001.
Meltzer, A. H. and S. F. Richard, "Tests of a Rational Theory of the Size of Government," *Public Choice*, 41, 403–18, 1983.
Mentzakis, E., M. Ryan, and P. McNamee, "Using Discrete Choice Experiments to Value Informal Care Tasks: Exploring Preference Heterogeneity," *Health Economics*, 20, 930–44, 2011.
Milesi-Ferretti, G. M., R. Perotti, and M. Rostagno, "Electoral Systems and Public Spending," *Quarterly Journal of Economics*, 117, 609–57, 2002.
Mitchell, R. C. and R. T. Carson, *UsingSsurveys to Value Public Goods: The Contingent Valuation Method*, 4th ed., Johns Hopkins University Press, Washington, 1989.
Mørkbak, M. R., S. B. Olsen, and D. Campbell, "Behavioral Implications of Providing Real Incentives in Stated Choice Experiments," *Journal of Economic Psychology*, 45, 102–16, 2014.
Neustadt, I. and P. Zweifel, "Income Redistribution: How to Divide the Pie?," MPRA Paper No. 35427, 2011.
———, "Is the Welfare State Sustainable? Experimental Evidence on Citizens' Preferences for Redistribution," *International Journal of Economics and Finance*, 7, 60–79, 2015.
Olson, M., *The Logic of Collective Action: Public Goods and the Theory of Groups*, A Harvard Paperback, HP 52, Harvard University Press, Cambridge, MA, 1965.
Perotti, R. and Y. Kontopoulos, "Fragmented Fiscal Policy," *Journal of Public Economics*, 86, 191–222, 2002.
Persson, T. and G. Tabellini, *The Economic Effects of Constitutions*, MIT Press, Cambridge, MA, 2003.
Pfarr, C., *Einkommen, Mobilität und individuelle Präferenzen für Umverteilung: Ein Discrete-Choice-Experiment, Dissertation, Beiträge zur Finanzwissenschaft*, 30, Mohr Siebeck, Tübingen, 2013.
Pfarr, C. and A. Schmid, "Redistribution Through Social Health Insurance: Evidence on Citizen Preferences," *European Journal of Health Economics*, 17, 611–28, 2016.
Phillips, K. A., R. F. Johnson, and T. Maddala, "Measuring What People Value: A Comparison of 'Attitude' and 'Preference' Surveys," *Health Services Research*, 37, 1659–79, 2002.
Pittau, M. G., R. Massari, and R. Zelli, "Hierarchical Modelling of Disparities in Preferences for Redistribution," *Oxford Bulletin of Economics and Statistics*, 75, 556–83, 2013.
Plotnick, R. D., "An Interest Group Model of Direct Income Redistribution," *Review of Economics and Statistics*, 68, 594, 1986.
Rabe-Hesketh, S., A. Skrondal, and A. Pickles, "Generalized Multilevel Structural Equation Modelling," *Psychometrika*, 69, 167–90, 2004.
———, "Maximum Likelihood Estimation of Limited and Discrete Dependent Variable Models with Nested Random Effects," *Journal of Econometrics*, 128, 301–23, 2005.
Ready, R. C., P. A. Champ, and J. L. Lawton, "Using Respondent Uncertainty to Mitigate Hypothetical Bias in a Stated Choice Experiment," *Land Economics*, 86, 363–81, 2010.
Richardson, J., "Government, Interest Groups and Policy Change," *Political Studies*, 48, 1006–25, 2000.

Roberts, K. W. S., “Voting Over Income Tax Schedules,” *Journal of Public Economics*, 8, 329–40, 1977.

Romer, T., “Individual Welfare, Majority Voting, and the Properties of a Linear Income Tax,” *Journal of Public Economics*, 4, 163–85, 1975.

Scarpa, R., S. Ferrini, and K. Willis., “Performance of Error Component Models for Status-quo Effects in Choice Experiments,” in R. Scarpa and A. Alberini, eds., *Applications of Simulation Methods in Environmental and Resource Economics, Economics of Non-Market Goods and Resources*, 6, 247–73, Springer, Dordrecht, 2005.

Scarpa, R., M. Thiene, and K. Train, “Utility in Willingness to Pay Space: A Tool to Address Confounding Random Scale Effects in Destination Choice to the Alps,” *American Journal of Agricultural Economics*, 90, 994–1010, 2008.

Statistisches Bundesamt, Statistisches Jahrbuch 2011, Wiesbaden, 2011.

Taylor, L. O., M. D. Morrison, and K. J. Boyle, “Exchange Rules and the Incentive Compatibility of Choice Experiments,” *Environmental and Resource Economics*, 47, 197–220, 2010.

Telser, H., *Nutzenmessung im Gesundheitswesen: Die Methode der Discrete-Choice-Experimente*, Kovac, Hamburg, 2002.

Train, K. E., *Discrete Choice Methods with Simulation*, 2nd, Cambridge University Press, New York, 2009.

Truman, D. B., *The Governmental Process: Political Interests and Public Opinion*, Knopf, 1951.

Vossler, C. A., M. Doyon, and D. Rondeau, “Truth in Consequentiality. Theory and Field Evidence on Discrete Choice Experiments,” *American Economic Journal: Microeconomics*, 4, 145–171, 2012.

Wedel, M., W. Kamakura, N. Arora, A. Bemmaor, J. Chiang, T. Elrod, R. Johnson, P. Lenk, S. Neslin, and C. Stig Poulsen, “Discrete and Continous Representation of Unobserved Heterogeneity in Choice Modeling,” *Marketing Letters*, 10, 219–32, 1999.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher’s website:

Appendix

Figure A.1: Model selection criteria

Table A.1: Attributes, labels and levels

Table A.2: Representativeness

Table A.3: Description of class membership variables.

Table A.4: Comparison of model fit statistics.

Table A.5: Marginal willingness to pay of three class latent class model accounting for expected benefits of redistribution

Table A.6: Three class latent class model without class membership variables

Table A.7: Three class latent class model accounting for expected benefits of redistribution