Essays on the Micro-Foundations of Welfare Attitudes and Polarization of Policy Preferences

by

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LIST OF ABBREVIATIONS

2SLS two stage least square

CAH class affinity hypothesis

dpGLM Dirichlet process generalized linear model

DPP Dirichlet process prior

EGP Erikson-Goldthorpe-Portocarero

ESeC European Socioeconomic Classification

ESS European Social Survey

FMM finite mixture model

FMMs finite mixture models

GLM generalized linear model

GLMM generalized linear mixed model

GLMMs generalized linear mixed models

GLMs generalized linear models

hdpGLM hierarchical Dirichlet process generalized linear model

HMC Hamiltonian Monte Carlo

HPD high posterior density

ISEI Socioeconomic Index of Occupational Status

ISSP International Social Survey Programme

IV instrumental variable

LIV latent instrumental variable

MLE maximum likelihood estimator

OUR Occupation Unemployment Rate

PCA Principal Component Analysis

MSI material self-interest

RMHMC Riemman manifold Hamiltonian Monte Carlo

RMSE root-mean-squared error

SCH social cognition hypothesis

SEP socioeconomic position

SES socioeconomic status

SfR support for redistribution

ABSTRACT

This dissertation comprises three essays on the micro-foundations voters' support for welfare policies. In the first paper, I propose a hierarchical Dirichlet process generalized linear model (hdpGLM) to deal with context-dependent latent heterogeneity in the effect of observed covariates. The model is motivated by the problem of investigating how people's socioeconomic characteristics affect their support for redistributive policies. The problem is that (1) many variables that condition the effect of observed socioeconomic characteristics of the individuals are latent or remain unmeasured, and (2) those latent conditioning features vary from country to country. The omitted variables can produce latent heterogeneity in the effect of observed covariates not only across countries but within each country as well. The proposed model allows us to investigate that context-dependent latent heterogeneity. It is general enough to be used with any hierarchical data in which the latent heterogeneity in the effect of lower-level characteristics is a function of upper-level features of the contexts, such as schools, hospitals, countries, or other institutional settings. The paper also shows how the model can be used to investigate the occurrence of Simpson's paradox in the context of generalized linear models.

In the second paper, I apply the hdpGLM approach to investigate the latent heterogeneity and polarization in voters' redistributive policy preferences. Previous studies only investigated polarization among observed socioeconomic groups (rich versus poor, white versus non-white), overlooking or ignoring within-group latent polarizations and cross-groups latent coalitions in policy preferences. The major contribution of the paper is a polarization model that uses the hdpGLM approach, accounts for latent heterogeneity in the determinants of redistributive preferences, and demonstrates how that heterogeneity

in the effect of observed covariates can lead to different latent structures of polarization in different political contexts.

In the third and final paper, I dive into the theoretical question of the association between socioeconomic positions and welfare preferences, which is the topic that motivated the first two methodological papers. The theoretical question I address is: What *explains* the negative association between socioeconomic positions and welfare policy preferences? That is, what is the mechanism that links socioeconomic positions to welfare policy preferences? The predominant explanation for that association is that people evaluate welfare policies from the point of view of their material self-interest. Looking at their own pocket, low-income groups see welfare policies as benefits for themselves, and high-income groups see that as cost and constraint to their consumption power. Based on political sociology and socially situated cognition literature, this paper questions that mechanism and argues that socioeconomic positions affect redistributive preferences in part because it affects perceptions about the socioeconomic environment and people's cognitive patterns of outcome attribution. Lower classes are more affected by the constraints imposed by external conditions, so they tend to attribute outcomes to exogenous forces rather than to individuals' agency, and they develop a more pessimistic perception about country's economy and unemployment. Those perceptions about the socioeconomic environment, affected by socioeconomic positions, affect redistribution preferences. The empirical analysis is based on a series of structural equations estimated using cross-national data from the European Social.

CHAPTER 1

Modeling Context-dependent Latent Heterogeneity

Abstract

Classical generalized linear models assume that marginal effects are homogeneous in the population given the observed covariates. Researchers can never be sure *a priori* if that assumption is adequately met. Recent literature in statistics and political science have proposed models that use Dirichlet process priors to deal with the possibility of latent heterogeneity in the covariate effects. In this paper, we extend and generalize those approaches and propose a hierarchical Dirichlet process of generalized linear models in which the latent heterogeneity can depend on context-level features. Such model is important in comparative analyses when the data comes from different countries and latent heterogeneity can be a function of country-level features. We provide a Gibbs sampler for the general model, a special Gibbs sampler for Gaussian-outcome variables, and a Hamiltonian Monte Carlo within Gibbs to handle discrete outcome variables. We demonstrate the importance of accounting for latent heterogeneity with a Monte Carlo exercise and with two applications that replicate recent scholarly work. We show how Simpson's paradox can emerge in the empirical analyses if latent heterogeneity is ignored and how the proposed model can be used to estimate heterogeneity in the effect of covariates.

1.1 Introduction

This paper proposes a model to deal with context-dependent latent heterogeneity in the effect of covariates in generalized linear models (GLMs). Generalized linear models, including those with mixed effects, are still one of the most used tools for multivariate analyses in political science. Among many assumptions required by such models, e.g., conditional independence, researchers need to assume that important covariates were not omitted. In that regard, much has been said in political science, statistics, and econometrics about the problems caused by omitting additive covariates in the model, but much less about the issues surrounding unobserved confounders that condition the effects of observed covariates. Conditioning features can lead to a well-known phenomenon in statistics called Simpson's paradox (a.k.a. aggregation paradox): an effect found when data are aggregated can be completely different or even reversed when data are separated into groups (Pearson, Lee and Bramley-Moore, 1899; Yule, 1903; Simpson, 1951; Blyth, 1972). The crucial point connecting the paradox and omitting variables is that, in the typical situation, researchers cannot be sure *a priori* whether there are latent or unobserved groups - a.k.a. clusters - with heterogeneous effect nor how many of them exist.

Consider for example the study of voter's preferences for redistribution. It is well known that features such as income and race can affect support for redistributive policies (Alesina and Angeletos, 2005; Rehm, 2009; Shayo, 2009; Alesina and Giuliano, 2010), but the effects of such observed factors like income and race can be heterogeneous among subpopulations due to unobserved factors such as motivation, personal history, and ability (Stegmueller, 2013). Consequently, the estimated effect of income, e.g., found when data are aggregated can be very different from the effect that would be estimated if we had observed motivation and considered low- and high-motivation groups separately or considered the income effect as conditional upon motivation.

Although that problem occurs in all scientific disciplines, perhaps it is more salient in the social sciences because, to mention a few reasons, problems have high dimensionality and often many dimensions remain unmeasured; data are often difficult to collect or are unavailable for privacy or other reasons; culture-specific aspects are not well measured; some subjects may conceal information from researchers purposefully; or researchers may simply be unaware of possible latent interactive factors (Stegmueller, 2013; Traunmuller, Murr and Gill, 2015).

Especially in comparative politics, an additional layer of complication seems likely: the latent heterogeneity can depend on context-level features. For instance, some researchers have shown that the effect of income is conditional on country-level variables such as the progressivity of the tax system (Beramendi and Rehm, 2016), the levels of inequality and crime rates (Rueda and Stegmueller, 2016), national identity (Johnston et al., 2010), and the existing levels of redistribution (Svallfors, 1997; Arts and Gelissen, 2001). If there is effect heterogeneity due to unobserved factors like motivation or personal experiential history among the population from a given context, say a country, it is very likely that a different heterogeneity manifests in other countries. In other words, suppose the effect of income on support for redistribution differs between two groups of voters (clusters) in the United States (the context) and we don't know the group membership of individual voters. We would expect there also to be heterogeneity among the population in another context, say Italy, but we wouldn't necessarily expect to find the same two latent groups in Italy (or in other contexts). Maybe there are more or fewer latent groups in Italy, and maybe some latent subpopulations are similar in Italy and the US. For instance, high- and low- motivation Italians and Americans may have welfare opinions similarly affected by their income, but Italians' personal experiences of crime may modify income effects on welfare support very differently than Americans' personal experiences of crime modify their income-effects on welfare support. In sum, the characteristics of the within-context heterogeneity (clustering) can vary from one context (e.g. country) to another, and that within-context heterogeneity may depend on the characteristics of the context itself; i.e., latent country-level factors may affect the number and nature (in terms of covariate effects) of the subpopulations found.

Practitioners in political science have long recognized these challenges. The possibility of omitting relevant conditioning factors, in conjunction with cross-context differences, has been stressed as an important source of an attitude of *radical skepticism* regarding the results of observational and experimental empirical investigation in the social sciences in general, and in comparative analysis in particular (Przeworski, 2007; Stokes, 2014).

The literature has proposed different approaches to address effect heterogeneity. The approaches depend on whether the grouping features are known and measured. When the groups are observed, classical approaches include mixed models with gaussian distributed random effects (e.g., hierarchical linear models (HLMs)). Suppose, for example, that we are analyzing data from many countries (contexts) and in each country there are different subpopulations with heterogeneous effects. If we knew the subpopulation to which each individual belongs, we could use a classical mixed-effects model at country and subpopulation levels. However, the distributional assumption on the random effects in such an approach is often criticized because of the single modality, light tails, and symmetry of the normal distribution, which imposes unnecessary and often unjustifiable constraints to the analysis in the empirical-modeling stage (Verbeke and Lesaffre, 1997; Heinzl and Tutz, 2013). Additionally, such an approach only works if the heterogeneous groups within each context are known and observed, and even so researchers also have to assume that there are no other latent or unobserved features that can cause effect heterogeneity. There are also some modeling approaches that work for single-context cases in which subpopulation membership is unknown or unobserved. When one wants to investigate subpopulations with latent heterogeneity within a given context and the number of subpopulations is known or assumed to be finite and fixed, a finite mixture model (FMM) is often used (Ng et al., 2006; De la Cruz-Mesía, Quintana and Marshall, 2008; Villarroel, Marshall and Barón, 2009). More commonly, however, researchers do not know if or how many latent heterogeneous subpopulations exist within a given context. Recent contributions in statistics have proposed models that use the Dirichlet process prior (DPP) to deal with these single-context cases with unknown subpopulation heterogeneity/clustering (Mukhopadhyay and Gelfand, 1997; Kleinman and Ibrahim, 1998*b*; Hannah, Blei and Powell, 2011; Heinzl and Tutz, 2013). Models using DPP have been used in the marketing literature to model the error term with a flexible distribution, the heterogeneity of consumer's demand in discrete choice models (Rossi, Allenby and McCulloch, 2012; Rossi, 2014), and in latent instrumental variable (LIV) models to deal with endogeneity of covariates (Ebbes et al., 2005; Ebbes, Wedel and Böckenholt, 2009). Related work has also been developed in econometrics and the program evaluation literature to study effect heterogeneity of training programs (Aakvik, Heckman and Vytlacil, 2005; Heckman and Vytlacil, 2007; Matzkin, 2007; Ichimura and Todd, 2007; Chen, 2007). DPP models have been applied in political science to study lengths of time political appointees stay in their appointed position (Gill and Casella, 2009), political priorities of senators (Grimmer, 2009), intraparty voting (Spirling and Quinn, 2010), immigrant turnout in elections (Traunmuller, Murr and Gill, 2015), and dynamic aspects of preferences for redistribution (Stegmueller, 2013).

Those DPP approaches, however, have three limitations. First, they are usually designed to be used with specific types of dependent variables, e.g. with outcome variables measured on an ordered scale. Second, particularly in political science literature, previous works have used DPP mostly as a prior only for the intercept (or error) term. Third and more importantly, previous works were not designed to study cases in which the latent heterogeneity is context-dependent.

To redress these limitations, this paper proposes a Dirichlet mixture of generalized linear models in which the within-context effect heterogeneity (clustering) can be context-dependent. The proposed model is a generalization, from the point of view of the expectation of the dependent variable, of usual GLMs, classical generalized linear mixed models (GLMMs), finite mixture models (FMMs), and current single-context Dirichlet mixtures of generalized linear models. The proposed model has several advantages over those special cases.

First, when there are multiple contexts, for instance in cross-country comparative analysis, the model can be used to investigate if country features are associated with latent heterogeneity in the covariate effects; that is, if country-level features affect the number and the characteristics of the subpopulation clusters.

Second, the proposed Dirichlet mixture of generalized linear models is developed in its full generality to handle Dirichlet mixtures of any distribution in the exponential family, to investigate heterogeneity not only in the error term but in the effect of any observed covariates, and, as mentioned, to study how such heterogeneity varies with context-level features. This paper implements two special cases: binary and continuous outcomes, modeled using Bernoulli and gaussian distributions, respectively. The algorithms for estimation of these special cases are presented, but an MCMC algorithm with a Gibbs sampler is derived for the more general model, so it can easily be extended to other outcome variable distributions.

Third, as a generalization of the other models, it can be used in situations where any of these more specialized models are well justified. If, in fact, one believes that a single GLM can be used across contexts and there is no latent heterogeneity in the population, the proposed model can be estimated and it will produce similar results for the conditional expectation of the dependent variable as those estimated using a generalized linear model (GLM). If there is just one context, but unknown clusters, it can be used instead of the single-context Dirichlet mixture of GLMs. The analogous situation is true for the other special cases, i.e., whenever the researcher is estimating a generalized linear mixed model (GLMM) or a finite mixture model (FMM) the proposed model can be used, and it has two additional advantages: the number of latent clusters, whose number is allowed to grow with the size of the data, is being simultaneously estimated, and as already mentioned, if the data comes from different contexts, the effect of the context on the characteristics of the clusters are also being investigated.

Fourth, the model estimates cluster memberships, so we can classify the data points into (latent) groups. The clusters differ in terms of the vector of linear coefficients that connect covariates to the outcome variable. So it can be used to study and characterize the heterogeneity in the effect of the covariates within and across contexts.

Fifth, the statistics literature has proposed approaches for dealing with Simpson's paradox based on domain knowledge (Hernán, Clayton and Keiding, 2011) and estimation diagnostics (Kievit et al., 2013). Its formal aspects and its connection to other problems have also been studied (Samuels, 1993; Pearl, 2011; Hernán, Clayton and Keiding, 2011;

Pearl, 2014). However, to the best of our knowledge, the literature hasn't proposed any modeling solution. We connect the model proposed here with Simpson's paradox in the context of generalized linear models and show how it can be used to detect the occurrence of the paradox and to deal with such problems by estimating the cluster-specific effects.

The rest of the paper is organized as follows. The next section presents the model, and the following section demonstrates how the proposed model is connected to classical GLM, mixed-models, FMM, and the econometric models mentioned above that use DPP to address heterogeneity in single-context analyses. Section 1.4 develops MCMC algorithms to estimate the model in its full generality and for two special cases of outcome variables. In section 1.5 we conduct a Monte Carlo exercise to study the frequentist properties of the estimation. The estimation is tested against a large variety of scenarios with and without latent heterogeneity. The section also illustrates how the model can be used to redress Simpson's paradox in the context of generalized linear models. It also compares the estimated results of GLM using a maximum likelihood estimator (MLE) with those produced by the proposed model using the MCMC developed in the section 1.4. Section 1.6 uses the model to analyze real data sets. It replicates some studies and shows how it uncovers latent heterogeneity and Simpson's paradox. Finally, the conclusions are presented.

1.2 The Model

To restate the problem, we want to use a generalized linear model to estimate the effect of the covariates X_i on y_i. Second, we want to take into account the possibility that the effect of the covariates is heterogeneous across different subgroups whose defining features are latent or were not observed. In other words, there might be latent subpopulations of individuals for which the covariates have different relationships with the outcome. Penultimately, we want to allow this latent subpopulation heterogeneity or clustering to be investigated both for data that comes from a single context or from multiple contexts. Finally, when the observed population comes from different contexts (e.g. different countries and different years), we want to investigate if context-level features change not only the effect of observed covariates on the outcome but also the existence and the characteristics of latent subpopulations in which the observed covariates have different effects.

The model that address all these issues can be developed as follows. For each unit i, suppose we have a set of observed covariates $X_i^{'} \in \mathbb{R}^{D_x}$ and an outcome variable y_i. Denote $X_i = (1, X_i^{'})$. Let K denote the number of heterogeneous groups in the population such that it can be bigger if the population is bigger, and let Z_i indicate the group of i. Z_i and K may or may not be known or observed. When Z_i is not observed, we use the term clusters instead of groups. Denote C_i the context of i, so $C_i = j$ indicates that the observation i comes from context indexed by $j \in \{1,...,J\}$, were J is the number of contexts.

For the purpose of illustration and as a toy example, suppose we want to investigate the effect of income and race on voters' support for welfare policies in different countries. Then X_i are measures of income and race of individual i, and y_i is his degree of support for welfare policies. The variable $C_i = j$ indicates the country where i lives, and data are collected in J countries. Suppose further that in each country the population is divided into *types* of individuals with different personal experiences with class and racial conflict. The types are not observed but we suspect the effect of income and race is conditional on the type. The latent variable $Z_i = k$ indicates that i is type k and K denotes the number of different types.

If $p()$ denotes a distribution in the exponential family, g a link function, and $\theta = (\beta, \sigma)$, the group and context specific GLM is given by:

$$y_i \mid Z_i, X_i, C_i, \theta_{C_i Z_i} \sim p(y_i \mid X_i, \theta_{C_i Z_i}) \quad \ni \quad \mathbb{E}[y_i \mid \cdot] = \mu_i = g^{-1}(X_i^T \beta_{C_i Z_i}) \quad , \quad Z_i = 1, ..., K \tag{1.1}$$

If Z_i was observed and K was therefore known, one could use classical mixed-effects models to estimate groups and context-specific heterogeneous effects. If K was known, but Z_i was latent or unobserved, one option would be to use finite mixture models for the estimation (Gaffney, 2003; Ng et al., 2006; De la Cruz-Mesía, Quintana and Marshall, 2008; Villarroel, Marshall and Barón, 2009). When Z_i is latent and K is unknown, some authors have proposed models that use DPP on θ in order to estimate cluster-specific effects[1] (Mukhopadhyay and Gelfand, 1997; Kleinman and Ibrahim, 1998*b*,*a*; Dorazio et al., 2008; Gill and Casella, 2009; Heinzl and Tutz, 2013; Stegmueller, 2013; Traunmuller, Murr and Gill, 2015). We refer here to such models as Dirichlet process generalized linear model (dpGLM), as adopted by Hannah, Blei and Powell (2011) (contrary to their formulation, however, we assume that X_i is given). If we denote by $\mathcal{DP}(\alpha, G)$ the Dirichlet process with location parameter α and base measure G, the GLM is modified in the following way to

[1]The clustering property of the DPP won't be revised here because there are already good sources explaining such feature of the Dirichlet process prior. The reader interested in a review can check Teh et al. (2006) and Müller and Mitra (2013) and the references therein.

produce the dpGLM:

$$
\begin{aligned}
&G \mid \alpha_o, G_o \sim \mathcal{DP}(\alpha_o, G_o) \\
&\theta_i \mid G \sim G \\
&y_i \mid X_i, \theta_i, \sim p(y_i \mid X_i, \theta_i) \quad , \quad \mathbb{E}[y_i \mid \cdot] = \mu_i = g^{-1}(X_i^T \beta_i)
\end{aligned}
\tag{1.2}
$$

Authors have warned that using DPP can lead to biased estimators, and it is known that neither weak consistency nor asymptotic unbiasedness are guaranteed in general in DPP models Diaconis and Freedman (1986); Ghosal, Ghosh and Ramamoorthi (1999); Tokdar (2006); Kyung et al. (2010). Although bias will always be present due to the bayesian priors, Hannah, Blei and Powell (2011) demonstrated that the dpGLM satisfies the conditions that guarantee weak consistency of the joint posterior distribution and consistency of the regression estimates (see also Tokdar (2006)).

The dpGLMs lacks the hierarchical clustering approach that we would like to have in the model, that is, that the clusters can be a function of higher-level context features in a multi-context analysis. We want to preserve the structure of the dpGLM and the DPP - because there might be unknown clusters with heterogeneous effect and unknown cluster membership - but include also such context-dependency - because the heterogeneity may depend on the context characteristics, observed and latent.

Some authors have proposed different approaches to model hierarchical clustering and to create dependencies among multiple Dirichlet processes (Mallick and Walker, 1997; Carota and Parmigiani, 2002; Müller, Quintana and Rosner, 2004; De Iorio et al., 2004; Teh et al., 2006). We can generalize and combine these approaches with the dpGLM in the following way. Let $W_j^{'} \in \mathbb{R}^{D_w}$ denote observed the context-level features of context j and J the total number of contexts as before. Let $W_j = (1, W_j^{'})$.

In our toy example, W_j could be, say, the level of economic development and inequality of the country (context) j, so that we can investigate whether and how the effect of income and race (the observed covariates $X_{i,}$) on support for redistribution (y_i) varies with the degree of economic development and inequality of the country (W_j). Moreover, we also want to investigate if the effect of those observed covariates (income and race) is different among within-country subpopulations whose membership (Z_i) is unobserved. Finally, we want to verify if those subpopulations vary from one country (context) to another due to a country's level of inequality and economic development (context-level features W_j).

The model can be modified in the following way to introduce such a context-level dependency among DPP:

$$
\begin{aligned}
& G_j \mid \alpha_o, G_o, W_j \sim \mathcal{DP}(\alpha_o, G_o(W_j)) \\
& \theta_{ji} \mid G_j \sim G_j \\
& y_i \mid X_i, C_i, \theta_{ji}, \sim p(y_i \mid X_i, \theta_{ji}) \quad , \quad \mathbb{E}[y_i \mid \cdot] = \mu_{ji} = g^{-1}(X_i^T \beta_{ji})
\end{aligned} \tag{1.3}
$$

We refer to the model (1.3) as hierarchical Dirichlet process generalized linear model (hdpGLM). It generalizes the GLM and the dpGLM and provides a hierarchical clustering structure that is context-dependent. Because it generalizes GLMs, it can be used even if there is neither heterogeneity nor multiple contexts. The advantage of using hdpGLM is that clusters and context dependency can be uncovered even if the researcher is uncertain about the existence of such heterogeneous effects. A model-selection procedure can be adopted to decide whether the results of GLM or hdpGLM is more adequate for the data at hand (Mukhopadhyay and Gelfand, 1997).

To complete the formulation of the model and connect (1.3) and (1.1), denote Z_{ik} the case in which individual i belongs to the subpopulation indexed by k, that is, $Z_i = k$. Let C_{ij} indicate that individual i belongs to the context (country) j, that is, $C_i = j$. We can parameterize the effect of the context-level covariates W with $\tau \in \mathbb{R}^{(D_w+1)\times(D_x+1)}$ and rewrite the model (1.3) using the stick-breaking construction (Sethuraman, 1994; Teh et al., 2006). The resulting model in its full generality is the following:

$$
\begin{aligned}
& V_l \mid \alpha_o \sim \text{Beta}(1, \alpha_o) \\
& \pi_k = \begin{cases} V_1 & , k = 1 \\ V_k \prod_{l=1}^{k-1} (1 - V_l) & , k > 1 \end{cases} \\
& Z_i \mid \pi \sim \text{Cat}(\pi) && , \quad \pi \in \Delta^\infty \\
& \tau_d \sim p(\tau_d) && , \quad d = 1, \ldots, D_x + 1 \\
& \theta_{kj} \mid Z_{ik}, \tau, C_{ij}, W \sim p(\theta_{jk} \mid W, \tau) && , \quad j = 1, \ldots, J \\
& y_i \mid Z_{ik}, \theta_{kj}, X_i, C_{ij} \sim p(y_i \mid Z_{ik}, C_{ij}, X_i, \theta_{kj}) && \ni \quad \mathbb{E}[y_i \mid Z_{ik}, \theta_{kj}, X_i, C_{ij}] = g^{-1}(X_i^T \beta_{kj}) \quad , \\
& && \quad p(y_i \mid Z_{ik}, C_{ij}, X_i, \theta_{kj}) \text{ from exponential family}
\end{aligned} \tag{1.4}
$$

We further assume that

$$
\begin{aligned}
\tau_d \mid \mu_\tau, \Sigma_\tau &\sim N_{D_w+1}(\mu_\tau, \Sigma_\tau) &, \quad d = 1, ..., D_x + 1 \\
\beta_{kj} \mid Z_{ik}, \tau, C_{ij}, W &\sim N_{D_x+1}([W_j^T \tau]^T, \Sigma_\beta) &, \quad j = 1, ..., J
\end{aligned}
$$

So, τ_d is a vector of linear coefficients on the country-level features. It determines the average effect of the individual level features X_{id} on the outcome y_i in the cluster k.

In our toy example, $\tau_1 = (\tau_{11}, \tau_{21})$ would be the linear effect of the inequality and economic development (the context-level features) on β_{1k}, the linear effect of income (observed covariate) on support for redistribution among people with similar history of social and racial conflict, which are unobserved, indexed by k. The parameter $\tau_2 = (\tau_{12}, \tau_{22})$ would be the linear effect of inequality and economic development on β_{2k}, which is the effect of race on support for redistribution among people of type k. Therefore, we have a DPP clustering model that is context-dependent as the linear coefficients β of the outcome variable depend on the cluster probability π, (thought Z_i) and on the context-level feature W (through its linear effect τ).

1.3 Generalized Linear Models, Finite Mixture Models, and hdpGLM

This section shows the relationship between the hdpGLM and the classical GLMs, GLMM, FMMs, and dpGLM in terms of the structure of the average parameters of the outcome variable y_i. In that sense, the hdpGLM can be viewed as a generalization of the other models. That generalization allows us to estimate latent or unobserved heterogeneity in the population in terms of how the covariates and the outcome are linearly related when the number of heterogeneous groups is not known in advance. The section also explores some connections between hdpGLM, LIV and latent-index models, which are approaches that use DPP with regression models.

As before, we denote $X_i = (1, X_i') \in \mathbb{R}^{(D_x+1)\times 1}$ the observed characteristics of unit i , $Z_i \in \{0,1\}^\kappa$ the design variable indicating the group (or cluster) of i. The parameter κ represents the number of clusters. Let $\gamma_i \in \mathbb{R}^{(D_x+1)\times\kappa}$ be the cluster-specific matrix of linear coefficients such that $\gamma_{ik} \in \mathbb{R}^{(D_x+1)\times 1}$ is the k^{th} column of γ_i with linear coefficients of cluster k. The most general formulation of the GLM in which every individual and groups have their own set of linear coefficients is:

$$y_i \mid X_i, \beta_i, \gamma_i \sim p(y_i \mid X_i, \beta_i, \gamma_i) \quad \ni \quad \mathbb{E}[y_i \mid \cdot] = \mu_i = g^{-1}(X_i^T \beta_i + X_i^T \gamma_i Z_i) \tag{1.5}$$

Define $\eta_i = X_i^T \beta_i + X_i^T \gamma_i Z_i$ and for simplicity let $D_x = 1$. We can write

$$\begin{aligned} \eta_i &= (\beta_{oi} + \gamma_{oi} Z_i) + (\beta_{1i} + \gamma_{1i} Z_i) X_i \\ \eta_{ik} &= (\beta_{oi} + \gamma_{oik}) + (\beta_{1i} + \gamma_{1ik}) X_i \end{aligned}$$

Classical GLMs, GLMMs, FMMs, or hdpGLMs emerge from model (1.5) depending on what we know or believe about κ, Z_i, γ_i and β_i. More precisely, it depends on the structural assumptions we impose on those parameters.

Classical GLM can be interpreted in two ways. Either one assumes $\gamma_i = 0$ for all i and $\beta_i = \beta$, which gives

$$\eta_i = \beta_o + \beta_1 X_i \tag{1.6}$$

or one assumes $\kappa = 1$, which gives

$$\eta_i = (\beta_o + \gamma_o) + (\beta_1 + \gamma_1) X_i = \theta_o + \theta_1 X_i \tag{1.7}$$

Clearly, (1.6) and (1.7) are structurally equivalent, and treating either θ in (1.7) or β in (1.6) as the parameter to be estimated should produce the same results.

When $\kappa > 1$, Z_i is observed, and one believes $\gamma \neq 0$, the common approach is to use fixed, random, or mixed effects models. For fixed effects, one either assumes that each group k has its own fixed intercept term θ_{ok}, or both its own fixed intercept and slope $(\theta_{ok}, \theta_{1k})$. Classical models with random effects similarly assume that each observed group has its own intercept (and slope) but also that, instead of being fixed, they are drawn from a common distribution. A gaussian distribution with zero mean is the standard choice for the random effects (Hayashi, 2000; Woodridge, 2002), but one can also have group-specific averages (Gelman and Hill, 2007) (see Table 1.1). Mixed models use a combination of random and fixed effects.

When Z_i is not observed, obviously it is not possible to use classical mixed models for the group heterogeneity. When one does not observe Z_i, but κ is known or it is assumed to be finite and fixed, then a finite mixture model is usually used (Lenk and DeSarbo, 2000). If we let $Z_i \sim \text{Cat}(\pi), \pi \in \Delta^{\kappa}$ then

$$\eta_i^{'} = \mathbb{E}[\eta_i \mid X_i] = (\beta_o + \gamma_o \pi) + (\beta_1 + \gamma_1 \pi) X_i = \theta_o + \theta_1 X_i \tag{1.8}$$

and

$$\eta_{ik}^{'} = \mathbb{E}[\eta_i \mid X_i] = (\beta_o + \gamma_o \pi_k) + (\beta_1 + \gamma_1 \pi_k) X_i = \theta_{ok} + \theta_{1k} X_i$$

which implies a finite mixture distribution for y_i, that is,

$$\begin{aligned} Z_i \mid \pi &\sim \text{Cat}(\pi), \pi \in \Delta^{\kappa} \\ y_i \mid X_i, Z_{ik}, \theta_k &\sim p(y_i \mid \mu_{ik}) \end{aligned} \tag{1.9}$$

By averaging over κ we get

$$\overline{\eta}_i^{'} = \overline{\theta}_o + \overline{\theta}_1 X_i$$

Again, it has the same basic structure of the classical GLM.

The dpGLM generalizes that structure by allowing κ to be undetermined. It emerges naturally from finite mixtures when there might be clusters in the populations that are latent or that weren't measured and, additionally, we do not know exactly the number of clusters. By letting $\kappa \to \infty$ in the finite mixture model in (1.9), and by putting a prior on θ and a stick-breaking prior on π we have the dpGLM, as described in (1.10) (Teh et al., 2006; Hannah, Blei and Powell, 2011).

$$
\begin{aligned}
&V_l \mid \alpha_o \sim \text{Beta}(1, \alpha_o) \\
&\pi_k = \begin{cases} V_1 & ,k = 1 \\ V_k \prod_{l=1}^{k-1}(1 - V_l) & ,k > 1 \end{cases} \\
&Z_i \mid \pi \sim \text{Cat}(\pi) \quad , \quad \pi \in \Delta^\infty \\
&\theta_{Zi} \mid Z_i \sim p_\theta \\
&y_i \mid X_i, Z_{ik}, \theta_k \sim p(y_i \mid \mu_{ik})
\end{aligned}
\tag{1.10}
$$

Starting with the dpGLM, by restricting the possible number of clusters to be finite ($\kappa < \infty$), and treating π and θ as fixed we are again back to the FMM. If, additionally, we either average out the clusters and treat those averaged elements as the fixed parameters to estimate or if $\kappa = 1$, we have the classical GLM. In sum, the GLMs and FMMs can be viewed special cases of the dpGLM.

Finally, the hdpGLM proposed here generalizes that structure to account for the possibility of context-dependent clustering. It does that by letting the linear coefficients of the clusters be a function of context-level covariates. We modify the model (1.10) by adding the parameter τ and context-level information W. Given J different contexts, the context level covariates $W \in \mathbb{R}^{J \times (D_w+1)}$, and the variable C_i that indicates the context to which i belongs, we have the hdpGLM model by modifying the dpGLM and adding the following structure to it:

$$
\begin{aligned}
&\tau_d \sim p(\tau_d) & , \quad d = 1, ..., D_x + 1 \\
&\theta_{Z_i C_i} \mid Z_{ik}, \tau, C_{ij}, W \sim p(\theta_{jk} \mid W, \tau) & , \quad j = 1, ..., J
\end{aligned}
\tag{1.11}
$$

Hence, if there is just one context ($J = 1$) we have the dpGLM again, through which is demonstrated the connection between hdpGLM and the other models. Table 1.1 summarizes the connections between the models.

The hdpGLM model is also structurally connected to latent instrumental variable (LIV) models (Ebbes, Böckenholt and Wedel, 2004; Ebbes et al., 2005; Ebbes, Wedel and Böckenholt, 2009). Such models can be used to deal with endogenous covariates. The main feature of the LIV is the introdution of a latent categorical instrumental variable, which turns the

Table 1.1: Relationship between GLM, GLMM, FMM and hdpGLM based on structural assumptions on κ, Z_i and φ_i.

Model(*)	κ (# of grupos)	Z_i (group indicator)	γ_i (group effect)	η_i (linear predictors)
GLM	known ($\kappa = 1$)	observed ($Z_i = 1$)	$\gamma_i = \gamma = 0$	$X_i\beta_1$
FE (I)	known ($\kappa = K \in \mathbb{N}$)	idem	$\gamma_{oi} = \gamma_{ok}, \gamma_{1ki} = 0$	$\beta_o + \gamma_{ok} + X_i\beta_1$
FE (I+S)	idem	idem	$\gamma_{oi} = \gamma_{ok}, \gamma_{1ki} = \gamma_{1k}$	$\beta_o + \gamma_{ok} + (\beta_1 + \gamma_{1k})X_i$
RE (I)	idem	idem	$\gamma_{oi} = \gamma_{ok}, \gamma_{1ki} = 0 \ni \gamma_{ok} \sim N(\mu_{\gamma_o}, \sigma_{\gamma_o})$	$\beta_o + \gamma_{ok} + X_i\beta_1$
RE (I+S)	idem	idem	$\gamma_{oi} = \gamma_{ok}, \gamma_{1ki} = \gamma_{1k} \ni \gamma_{dk} \sim N(\mu_{\gamma_d}, \sigma_{\gamma_d})$	$\beta_o + \gamma_{ok} + (\beta_1 + \gamma_{1k})X_i$
FMM	idem	unobserved/latent	$\gamma_{oi} = \gamma_{ok}, \gamma_{1ki} = \gamma_{1k}$	$\beta_o + \sum_{k=1}^{K} Z_{ik}\gamma_{ok} + (\beta_1 + \sum_{k=1}^{K} Z_{ik}\gamma_{1k})X_i$
hdpGLM	unkown ($\kappa \in \mathbb{N} \cup \{\infty\}$)	unobserved/latent	idem	$\beta_o + \sum_{k=1}^{\kappa} Z_{ik}\gamma_{ok} + (\beta_1 + \sum_{k=1}^{\kappa} Z_{ik}\gamma_{1k})X_i$

(*) GLM: Generalized Linear Models; FE: Fixed Effect in the intercept (FE (I)) and both in the intercept and slope (FE (I+S)); RE: Random Effect in the intercept (FE (I)) and both in the intercept and slope (RE (I+S)); FMM: finite mixture models

instrumental variable (IV) regression model into a FMM. To see this, consider this simple example of a classical IV model with endogenous covariate x_1, a gaussian outcome, and the instrumental variable z (index i omitted for simplicity) :

$$\begin{cases} y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \\ x_1 = \gamma_0 + \gamma_2 x_2 + \gamma_3 z + \nu \end{cases} \tag{1.12}$$

For $\phi_0 = \beta_0 + \beta_i \gamma_0$, $\phi_2 = \beta_1 \gamma_2 + \beta_2$, $\phi_3 = \beta_1 \phi_3$, and $\varepsilon' = \beta_1 \nu + \varepsilon$ we have the reduced form:

$$y = \varphi_0 + \varphi_2 x_2 + \varphi_3 z + \varepsilon' \tag{1.13}$$

The LIV approach defines a latent K-level categorical random variable Z_i to be used instead of the instrument z_i. Each group k is assumed to have its is own mean value φ_{0k}. It leads to a FMM with K latent groups such that the outcome is given by:

$$y = (\varphi_0 + \varphi_{0k}) + \varphi_2 x_2 + \varepsilon' = \theta_{0k} + \theta_2 x_2 + \varepsilon' \tag{1.14}$$

or equivalently, and assuming group-specific errors:

$$\begin{aligned} y &= \beta_0 + \beta_1 x_{1k} + \beta_2 x_2 + \varepsilon \\ x_{1k} &= \gamma_0 + \gamma_2 x_2 + \varphi_{0k} + \nu_i \end{aligned} \tag{1.15}$$

Ebbes, Wedel and Böckenholt (2009) and Ebbes et al. (2005) have proposed (1.15), called LIV, to deal with endogeneity in the regressors. Obviously, by (1.14) and (1.15) we can see how it is structually connected to the hdpGLM. Some differences between LIV and the model presented here is that in the former the number of latent groups needed to be selected in advance before the parameters are estimated, which is a feature of any FMM. Moreover, LIV is designed for a single-context estimation, that is, the endogeneity and the instrument are not context-dependent. The main difference, however, is that the LIV approach uses the joint distribution of the endogenous covariates and the outcome due to its goal of dealing with endogeneity of the covariate, while here the covariates are assumed to be exogeneous. The hdpGLM leads to a LIV model if we truncate the DPP, restrict the hdpGLM to its non-hierarchical version (dpGLM) with gaussian outcome, and model the distribution of the endogenous covariates as in the equations above.

Finally, the hdpGLM also has a close connection with the latent-index model that has been designed to deal with single-context heterogeneity (Aakvik, Heckman and Vytlacil, 2005; Rossi, 2014). Aakvik, Heckman and Vytlacil (2005) propose a model in which the marginal effects are heterogeneous in the population and indexed by a continuous latent random variable. They also provide a special case with two latent groups by using a binary transformation of that (gaussian distributed) latent index, which produces a mixture model with two latent components. The model here generalizes that continuous latent index approach in two ways. First, it imposes a much more flexible distribution on the latent index and allows us to estimate effect heterogeneity when there are unknown number of finite or countably infinite, groups. Their gaussian index model can be approximated by a countably infinity partition of the real line and a simetric unimodal discrete distribution on that partition. It is embedded in the structure of the model and the DPP can naturally be used to estimate such a distribution of the indexes. Second, the model here generalizes their approach by adding a context-dependent structure to the latent heterogeneity.

1.4 Estimation

There are a variety of options in the literature to estimate models that use DPP (Ishwaran and Zarepour, 2000; Neal, 2000; Blei, Jordan et al., 2006; Walker, 2007). Here we extend the approach proposed by Ishwaran and James (2001). In order to implement a (blocked) Gibbs sampler for a DPP model, one of the algorithms they propose uses a truncated version of the stick-breaking construction in conjunction with the generalized Dirichlet distribution. We extend their basic algorithm in two ways. First, we incorporate the hierarchical structure of the model proposed here and develop a Gibbs sampler in its full generality. Second, we derive the sampler for two special cases: continuous outcome variable y_i, modeled using a gaussian distribution, and a binary outcome variable, modeled using a Bernoulli distribution with a logistic transformation of the average parameter. For the gaussian outcome, the Gibbs update can be used for all parameters. Therefore, in practice for that special case, the estimation shows good convergence diagnostics within thousand iterations and it can be performed in a relatively short time depending on the size of the data set. For the binary outcome, the Gibbs update is available for all parameters but the linear coefficients of the generalized linear model. So we extend the algorithm and implement a Metropolis-Hasting update within Gibbs to sample the linear coefficients (β) using Riemann manifold Hamiltonian Monte Carlo (Neal, 2000; Shahbaba and Neal, 2009; Neal et al., 2011). The R package hdpGLM contains the implementation of the model with the algorithms presented here.

The truncation of the DPP used in the MCMC algorithm restricts the mixing probability parameter $\pi \in \Delta^{\infty}$ described in (A.6) to $\pi \in \Delta^{K}$. To estimate the model properly, we set a large value for K and monitor the estimation to check the maximum number of clusters the sampler used to allocate the data points during the iterations. If it reached K at any point we increase its value and repeat the process. By selecting a K much larger than the number of clusters the sampler activates during the estimation, we make sure the truncation is not changing the estimated results.

As before, let $\mathbf{X} \in \mathbb{R}^{n\times(D_x+1)}$ denote the individual level covariates including a column with ones for the intercept term, and n the number of data points including all contexts. Denote $C = (C_1, ...C_n)$ and $C_i \in \{1, ..., J\}$ the variable that indicates the context to which i belongs, and let $\mathbf{W} \in \mathbb{R}^{J\times(D_w+1)}$ be the $(D_w+1)-$dimensional context-level features of the contexts J. Finally, let $Z = (Z_1, ..., Z_n)$.

The following additional notation is used to derive the algorithm: Z^* denotes the unique values of Z, and Z^{*C} the values between 1 and K that are not in Z^*. We denote by Z_j^* the unique values of Z in the context j, and Z_j^{*C} its complement in j, I_k is the set of indexes i of the data points assigned to the cluster k, N_k the total number of data points in k, and X_{jk} (or y_{jk}) the covariates (outcome variable) of the units i in context j and cluster k.

Given the most general formulation of the hdpGLM in (A.6) and the truncation used for the sampler we have the following proposition (see proof in the appendix A.1):

Proposition .1 (Blocked Giibs sampler for hdpGLM)**.** *A Blocked Gibbs sampler for the model described in (A.6) with $\pi \in \Delta^K$ is given by the algorithm 1.*

Algorithm 1 Gibbs Sampler for hdpGLM

Require: $Z^{(t)} = (Z_1^{(t)}, ..., Z_n^{(t)}), \theta_{Z_i}^{(t)}, \tau^{(t)}, \pi^{(t)}$

1: For $d \in \left\{1, ..., D_x + 1\right\}$, sample $\tau_d^{(t+1)} \mid \theta^{(t)}, \mathbf{W} \sim p(\theta_d^{(t)} \mid \mathbf{W}, \tau_d^{(t)}) p(\tau_d)$

2: For $j = 1, ..., J$

For all $k \in Z_j^*$ sample $\theta_{kj}^{(t+1)} \mid Z^{(t)}, \theta^{(t)}, \tau^{(t+1)}, \mathbf{X}, \mathbf{W}, C, y \sim p(\theta_{kj} \mid \tau^{(t+1)}, \mathbf{W}) \prod_{i \in I_k} p(y_i \mid Z_{ik}^{(t)}, C_{ij}, X_i, \theta_{kj}^{(t)})$

For all $k \in Z_j^{*C}$ sample $\theta_{kj}^{(t+1)} \mid \tau^{(t+1)}, \mathbf{W} \sim p(\theta_{kj} \mid \tau^{(t+1)}, \mathbf{W})$

3: For $i = 1, ..., n$, sample $Z_i^{(t+1)} \mid \theta^{(t+1)}, \pi^{(t)}, X_i, y \sim \sum_{k=1}^{K} p_{ik} \delta(Z_{ik}) \ni p_{ik} \propto \pi_k^{(t)} p(y_i \mid X_i, Z_{ik}^{(t)}, C_{ij}, \theta_{kj}^{(t+1)})$

4: For $k = 1, ..., K-1$ sample $v_k^{(t+1)} \overset{iid}{\sim} \text{Beta}\left(1 + N_k^{(t+1)}, \alpha + \sum_{l=k+1}^{K} N_l^{(t+1)}\right) \ni N_k^{(t+1)} = \sum_{i=1}^{n} I(Z_{ik}^{(t+1)})$

Set $v_K^{(t+1)} = 1$ and compute $\pi_k^{(t+1)} = \begin{cases} v_1^{(t+1)} & ,k=1 \\ v_k^{(t+1)} \prod_{l=1}^{k-1} (1 - v_l^{(t+1)}) & ,k = 2, ..., K \end{cases}$

A special case of the model described in (A.6) occurs when y_i is gaussian distributed. Let $N_d(\mu, \Sigma)$ denote a d-dimensional multivariate gaussian distribution. Then, for $\theta = (\beta, \sigma)$, we can have a Gibbs sampler for all parameters if we use the following distribution for τ, β and σ (see proof in the appendix A.1):

$$
\begin{aligned}
\tau_d \mid \mu_\tau, \Sigma_\tau &\sim N_{D_w+1}(0, \Sigma_\tau) && , \quad d = 1, ..., D_x + 1 \\
\beta_{kj} \mid Z_{ik}, \tau, C_{ij}, \mathbf{W} &\sim N_{D_x+1}([W_j^T \tau]^T, \sigma_\beta I) && , \quad j = 1, ..., J, k = 1, ..., K \\
\sigma_k^2 \mid Z_{ik} &\sim \text{Scale-inv-}\chi^2(\nu, s^2) \\
\varepsilon_i \mid \sigma_k, Z_{ik} &\sim N(0, \sigma_k) \\
y_i &= X_i^T \beta_{Z_i C_i} + \varepsilon_i
\end{aligned}
\tag{1.16}
$$

Proposition .2 (Gibbs for hdpGLM with gaussian mixtures)**.** *The Gibbs sampler for the model described in (1.16) is given by the algorithm 2.*

Algorithm 2 Gibbs Sampler for the hdpGLM with gaussian mixtures

Require: $Z^{(t)} = (Z_1^{(t)},...,Z_n^{(t)}), \theta_{Z_i}^{(t)}, \tau^{(t)}, \pi^{(t)}$

1: For all $d \in \{1,...,D_x+1\}$ sample $\tau_d^{(t+1)} \mid \beta^{(t)}, \mathbf{W} \sim N(\bar{\mu}_{\tau_{dj}}, \bar{\Sigma}_{\tau_d}) \quad \ni$

$\bar{\mu}_{\tau_{dj}} = \frac{1}{K}\sum_{k=1}^{K}\mu_A^{(k)}$; $\bar{\Sigma}_{\tau_d} = \frac{1}{K}\Sigma_A$; $S_A = \left(\Sigma_\tau^{-1}\sigma_\beta^2 + \mathbf{W}^T\mathbf{W}\right)^{-1}$; $\mu_A^{(k)} = S_A\mathbf{W}^T\beta_{dk}^{(t)}$; $\Sigma_A = S_A\sigma_\beta^2$

2: For $j = 1,...,J$

For all $k \in Z_j^*$ sample $\beta_{kj}^{(t+1)} \mid Z^{(t)}, \sigma^{2(t)}, \tau^{(t+1)}, \mathbf{X}, \mathbf{W}, C, y \sim N_{D+1}(\bar{\mu}_\beta, \bar{\Sigma}_\beta) \quad \ni$

$S_\beta = \left(\Sigma_\beta^{-1}\sigma_k^2 + X_{kj}^T X_{kj}\right)^{-1} \quad , \quad \bar{\mu}_\beta = S_\beta\left[\Sigma_\beta^{-1}(\mathbf{W}^T\tau^{(t+1)})^T + \frac{X_{kj}^T y_{kj}}{\sigma_k^{2(t)}}\right]\sigma_k^2 \quad ; \quad \bar{\Sigma}_\beta = S_\beta\sigma_k^{2(t)}$

For all $k \in Z_j^{*C}$ sample $\beta_{kj}^{(t+1)} \mid \tau^{(t+1)}, \mathbf{W} \sim N_{D+1}((\mathbf{W}^T\tau^{(t+1)})^T, \Sigma_\beta)$

3: For all $k \in Z^*$ sample $\sigma_k^{2(t+1)} \mid Z^{(t)}, \beta^{(t+1)}, \tau^{(t+1)}, \mathbf{X}, \mathbf{W}, C, y \sim \text{Scale-inv-}\chi_2(\bar{\nu}, \bar{s}^2) \quad \ni$

$\bar{\nu} = \nu + N_k^{(t)} \quad ; \quad \bar{s}^2 = \frac{\nu s^2 + N_k^{(t)}\hat{s}^2}{\nu + N_k^{(t)}} \quad ; \quad \hat{s}^2 = \frac{1}{N_k^{(t)}}(y_k - X_k\beta_k^{(t+1)})^T(y_k - X_k\beta_k^{(t+1)})$

Forall $k \in Z^{*C}$ sample $\sigma_k^{2(t+1)} \mid Z_i = k \sim \text{Scale-inv-}\chi^2(\nu, s^2)$

4: For $i = 1,...,n$, sample $Z_i^{(t+1)} \mid \theta^{(t+1)}, \pi^{(t)}, X_i, y \sim \sum_{k=1}^{K} p_{ik}\delta(Z_i = k) \ni p_{ik} \propto \pi_k^{(t)} p(y_i \mid X_i, Z_{ik}^{(t)}, C_{ij}, \theta_{kj}^{(t+1)})$

5: For $k = 1,...,K-1$ sample $v_k^{(t+1)} \overset{iid}{\sim} \text{Beta}\left(1 + N_k^{(t+1)}, \alpha + \sum_{l=k+1}^{K} N_l^{(t+1)}\right) \ni N_k^{(t+1)} = \sum_{i=1}^{n} I(Z_{ik}^{(t+1)})$

Set $v_K^{(t+1)} = 1$ and compute $\pi_k^{(t+1)} = \begin{cases} v_1^{(t+1)} & ,k=1 \\ v_k^{(t+1)}\prod_{l=1}^{k-1}(1 - v_l^{(t+1)}) & ,k=2,...,K \end{cases}$

When the outcome variable y_i in the model (A.6) is binomial distributed, or in general has a distribution that does not have a conjugate prior for the linear coefficients, the full conditional of the parameters θ (or β) is not standard and we cannot sample from it directly. To deal with such cases we use a Riemman manifold Hamiltonian Monte Carlo (RMHMC) update (Girolami and Calderhead, 2011) within Gibbs to sample the β coefficients. We can still sample all the other parameters as before. For the sake of completeness, the RMHMC algorithm is presented in the appendix.

The random variable of interest is $\beta_{kj} \in \mathbb{R}^{D_x+1}$, called the position variable of the Hamiltonian Monte Carlo (HMC) algorithm (Neal et al., 2011), and we denote by $v \in \mathbb{R}^{D_x+1}$ the ancillary variable (momentum) such that $v \sim N_{D_x+1}(0, G(\beta_{kj}))$. The Hamiltonian for our model is defined by

$$
\begin{aligned}
H(\beta_{kj}, v) = U(\beta_{kj}, v) + K(\beta_{kj}, v) = & -\ln p(\beta_{kj} \mid \cdot) + \frac{D_x+1}{2} \ln(2\pi) \\
& + \frac{1}{2}\left[\ln\left(\det[G(\beta_{kj})]\right) + v^T G(\beta_{kj})^{-1} v\right]
\end{aligned}
\tag{1.17}
$$

whose solution is

$$
\begin{aligned}
\nabla_v H(\beta_{kj}, v) &= G(\beta_{kj})^{-1} v \\
\nabla_{\beta_{kj}} H(\beta_{kj}, v) &= -\Bigg[\nabla_{\beta_{kj}} U(\beta_{kj}, v) - \frac{1}{2}\operatorname{tr}\left\{G(\beta_{kj})^{-1}\nabla_{\beta_{kj}} G(\beta_{kj})\right\} \\
&\qquad + \frac{1}{2}\left(v^T G(\beta_{kj})^{-1} G(\beta_{kj})^{-1} v\right) \nabla_{\beta_{kj}} G(\beta_{kj})\Bigg]
\end{aligned}
\tag{1.18}
$$

The Hamiltonian equations are solved using the generalized Stormer-Verlet leapfrog integrator (Calin and Chang, 2006; Girolami and Calderhead, 2011). For L leapfrog steps with size ε, and $l = 1, \ldots L$, it is given by:

$$
\begin{aligned}
v^{l+\frac{\varepsilon}{2}} &= v^l - \frac{\varepsilon}{2}\nabla_{\beta_{kj}} H\left(\beta_{kj}^l, v^{l+\frac{\varepsilon}{2}}\right) \\
\beta_{kj}^{l+\varepsilon} &= \beta_{kj}^l + \frac{\varepsilon}{2}\left[\nabla_v H\left(\beta_{kj}^l, v^{l+\frac{\varepsilon}{2}}\right) + \nabla_v H\left(\beta_{kj}^{l+\varepsilon}, v^{l+\frac{\varepsilon}{2}}\right)\right] \\
v^{l+\varepsilon} &= v^{l+\frac{\varepsilon}{2}} - \frac{\varepsilon}{2}\nabla_{\beta_{kj}} H\left(\beta_{kj}^{l+\varepsilon}, v^{l+\frac{\varepsilon}{2}}\right)
\end{aligned}
\tag{1.19}
$$

When y_i is binomial, that is, the distribution of y_i in the model (A.6) is defined by

$$
y_i \sim \text{Bin}(p_{kj}) \quad , \quad p_{kj} = \frac{1}{1 + e^{-X_i^T \beta_{kj}}}
$$

then, given the equation (A.4), the elements of the RMHMC for the model hdpGLM when $k \in Z_j^*$ are defined by the following equations:

$$
\begin{aligned}
U(\beta_{kj}) = -\ln p(\beta_{kj} \mid \cdot) \propto -\Bigg[&- \frac{D_x+1}{2}\ln 2\pi - \frac{1}{2}\ln(\det(\Sigma_\beta)) \\
&- \frac{1}{2}(\beta_{kj} - (W_j^T\tau)^T)^T \Sigma_\beta^{-1}(\beta_{kj} - (W_j^T\tau)^T) \\
&- \sum_{i\in I_k} y_i \ln\left(1 + e^{-X_i^T\beta_{kj}}\right) - \sum_{i\in I_k}(1-y_i)\ln\left(1+e^{X_i^T\beta_{kj}}\right)\Bigg] \\
\nabla_{\beta_{kj}} U(\beta_{kj}) = -\Bigg[&-(\beta_{kj} - (W_j^T\tau)^T)^T\Sigma_\beta^{-1} + \sum_{i\in I_k} X_i y_i p(y_i = 0 \mid \cdot) - \sum_{i\in i_k} X_i(1-y_i)p(y_i = 1 \mid \cdot)\Bigg]
\end{aligned}
$$

In practice we use $G(\beta_{kj}) = I_{(D_x+1)\times(D_x+1)}$, which is the most widely used approach in applications (Neal et al., 2011; Liu, 2008). It also simplifies the equations (A.7), (A.8), and (A.9) substantially. Using $v \sim N_{D_x+1}(0, I)$, the integrator reduces to the standard Stormer-Verlet leapfrog integrator (Duane et al., 1987; Neal et al., 2011). We follow that approach in this paper.

1.5 Monte Carlo Simulation

In this section, we conduct a Monte Carlo exercise[2] to demonstrate the properties of the estimates of the model produced by the algorithms developed in Section 1.4. The exercise is divided into three parts. First, we reproduce a particular situation that often occurs in practice if one omits factors that condition the association between the variable of interest and the outcome. In order to do that, we compare results produced by hdpGLM with those produced by GLM when there is no latent heterogeneity in the population and when there are latent clusters. We show how the Simpson's paradox can happen in the latter case and how it is uncovered by the proposed model. In the second part of the MC exercise we simulate a large variety of possible scenarios, each with different types of heterogeneity and numbers of observed covariates to show that the model has good performance in a large variety of situations. We evaluate the frequentist properties of the estimators in each case, particularly their coverage probability (Little et al., 2011; Carlin and Louis, 2000). Lastly, we compare the predictive performance of GLM and hdpGLM for different possible number of clusters in terms of root-mean-squared error (RMSE).

[2]See Ferrari (2018) for replication.

We start by comparing the estimates produced by GLM and by hdpGLM with and without latent heterogeneity in the population. We generated data sets from two parameter configurations with 3 continuous covariates sampled from a gaussian distribution. In the first data set, there is no effect heterogeneity. Hence, a single GLM would be appropriate because the effect of those three covariates are homogeneous in the population. In the second data set, we let the effect of one covariate to be conditional on a latent factor such that it has opposite signs and similar magnitude for half of the population. The effect of the other two covariates is homogeneous. Data sets used in this exercise contain 2000 observations.

As a toy example, we can think that the first covariate represents income, the second age, the third the degree of racial fragmentation in the neighborhood, and the outcome the degree of support for redistributive policies. The effect of income on support for redistribution depends on a latent feature, let's say, if the individuals have experienced economic reward due to their effort and hard work, as opposed to luck or family monetary heritage. The latent heterogeneous effect of income can occur, for instance, if more income means less support for redistribution only for those that believe upward mobility can be achieved through effort and hard work.

Table 1.2 compares the point estimates and their confidence intervals produced by estimating a GLM using MLE, with the posterior average and the 95% HPD interval produced by estimating the hdpGLM with the MCMC proposed here. We can compare the estimates with the true value, which is displayed in the fourth column of the table. After estimating the hdpGLM, we classified the data into clusters using the estimated cluster probability of each data point. We assigned each observation to the cluster they have the highest probability to belong to. The indexes of the clusters occupied by data points are displayed in the first column of the table. We can see in the upper half of the Table 1.2 the estimates when the data comes from a population in which there is no heterogeneity. All data points were classified into the same single cluster by the hdpGLM. The estimates of the two models are very similar. The lower half of the table presents the results of the estimation using GLM and hdpGLM for the second data set with heterogeneous effects in the first covariate X_1. We used the same procedure just described to classify the data into clusters. The hdpGLM estimated two clusters in virtually all repetitions of the procedure. The results produced by the GLM and the hdpGLM are very similar for the covariates 2 and 3 (β_3 and β_4), whose effects are homogeneous in the population. For the hdpGLM, the values of the linear effect of those covariates with homogeneous effects are indistinguishable

Table 1.2: Comparing estimates of GLM (estimated using MLE) and hdpGLM (estimated using MCMC) with and without latent heterogeneity in the population.

				hdpGLM with MCMC estimates		GLM with MLE estiates	
Cluster	Covariate	Parameter	True	MCMC Mean	95% HPD	MLE estimate	95% CI
No latent heterogeneity in the population ($K=1$)							
1	(Intercept)	β_0	-0.15	-0.16	(-0.21, -0.12)	-0.16	(-0.21, -0.12)
1	X_1	β_1	-3.09	-3.11	(-3.15, -3.07)	-3.11	(-3.15, -3.07)
1	X_2	β_2	9.90	9.91	(9.86, 9.95)	9.91	(9.86, 9.95)
1	X_3	β_3	3.90	3.87	(3.83, 3.92)	3.87	(3.83, 3.92)
Two supbopulations ($K=2$) with heterogeneous effect on X_1							
1	(Intercept)	β_0	-3.30	-3.23	(-3.30, -3.14)	-3.25	(-3.34, -3.17)
1	X_1	β_1	2.00	2.00	(1.93, 2.08)	0.16	(0.08, 0.25)
1	X_2	β_2	-5.29	-5.31	(-5.39, -5.23)	-5.33	(-5.41, -5.24)
1	X_3	β_3	2.25	2.29	(2.21, 2.36)	2.23	(2.14, 2.32)
2	(Intercept)	β_0	-3.30	-3.28	(-3.35, -3.21)	–	–
2	X_1	β_1	-1.50	-1.52	(-1.58, -1.45)	–	–
2	X_2	β_2	-5.29	-5.29	(-5.37, -5.24)	–	–
2	X_3	β_3	2.25	2.19	(2.11, 2.26)	–	–

in the two clusters estimated, as expected. However, for the heterogeneous effect β_1 (e.g., income) the GLM estimated a positive effect when in fact there are two subpopulations, one with a positive and another with a negative effect. The hdpGLM, on the other hand, estimated the marginal effect of X_1 correctly for both clusters.

Table 1.2 contains an example of the Simpson's paradox: the aggregate effect found for X_1 when one uses GLM and ignores the clusters is quite different from the effect found when the clusters are considered. We can see it more clearly in Figure 1.1. The lines represent the fitted values using the MLE estimate for the GLM model and the fitted values using the posterior average for the hdpGLM. In the left panel, we can compare the estimated marginal effects produced by each model. In the right panels, we see the data points after they were clustered by the hdpGLM. The right panels also display the fitted values. We would have reached incomplete conclusions using GLM in such situation: the effect is positive and significant for the MLE estimates of the GLM but, in fact, it is negative for half of the population, and it has a larger positive effect than estimated by the GLM for the other half.

The general take away from these results is that when GLM is well specified and there is no effect heterogeneity due to latent features, using hdpGLM won't harm the estimation. When there are clusters with heterogeneous effects, GLM will produce accurate aggregate results but can nevertheless be incorrect for each one of the subpopulations. Table 1.2 and

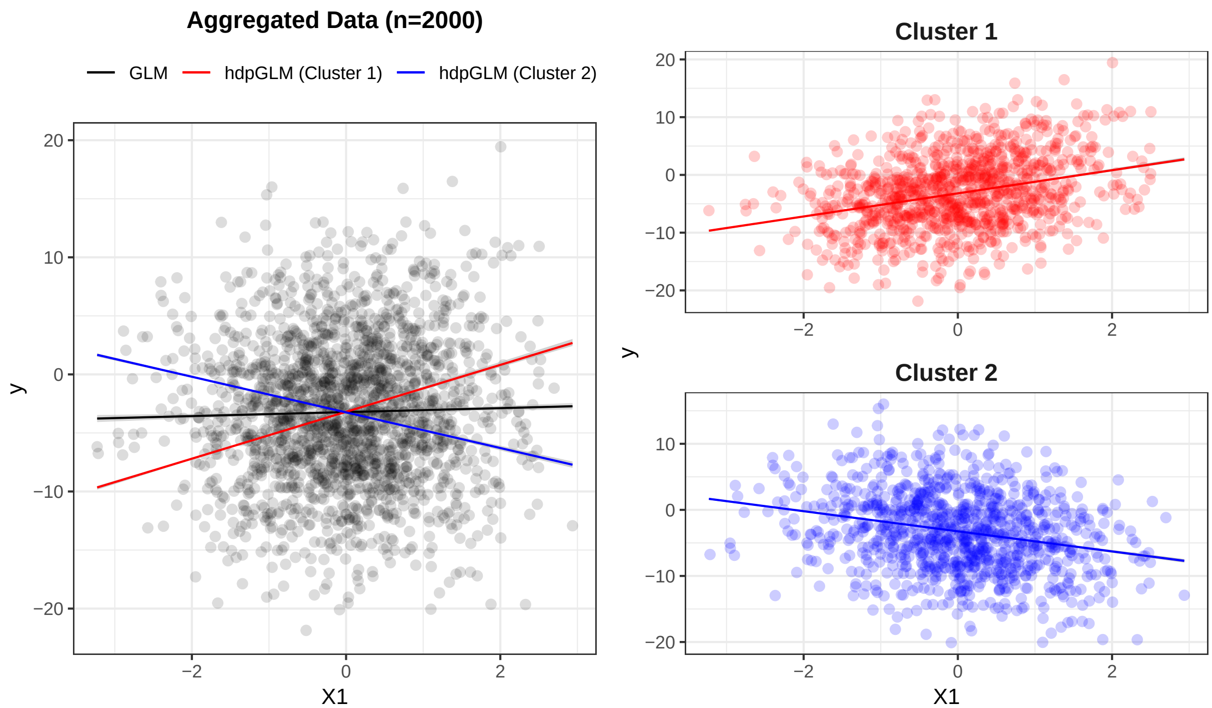


Figure 1.1: Comparing marginal effect estimated using GLM (MLE estimator) and hdpGLM (MCMC posterior average) when there are 3 clusters in the population.

Figure 1.1 demonstrate that the hdpGLM reduces to GLM when there is no heterogeneity (see Section 1.3). When the assumptions that justify the adoption of the GLM holds, the hdpGLM can still be used and it estimates the mean value of the linear parameters quite close to the ones produced by MLE estimates of GLM. When there was heterogeneity, the hdpGLM classified the data correctly into two clusters, the marginal effects were correctly estimated, and the Simpson's paradox was uncovered.

Next, in order to evaluate the performance of the hdpGLM in a wide range of possible scenarios, we randomly generated 10 different sets of parameters. To make the Monte Carlo exercise faster and easy to visualize, we simulate data for a single context ($J = 1$) with a continuous outcome variable. An example with context-dependent heterogeneity ($J > 1$) are presented in the sequel. Examples with binary outcome variables are provided in the appendix.

For each parameter set, we randomly generated data sets. The number of clusters K and the number of covariates in each case was also randomly generated. We allowed the heterogeneity to occur in the effect of all covariates. Values of the linear coefficients range from -20 to 20. We estimated the hdpGLM for each one of the data sets and all the usual convergence diagnostics were conducted (Geweke, 1992; Cowles and Carlin, 1996; Brooks and Gelman, 1998; Flegal, Haran and Jones, 2008; Flegal, 2008). The high posterior density (HPD) intervals were computed across data sets generated by each parameter set and so was the posterior average.

Table 1.3 summarizes the coverage probability of the linear coefficients $\boldsymbol{\beta}$ for each one of the 10 parameter sets along with the cluster estimation. The first column indicates the number of covariates in each parameter set, and the second indicates the true number of clusters in the population. The third through fifth columns display the summaries of the estimation across the 100 data sets generated by each parameter set. It shows the mean, minimum, and maximum number of clusters the data points were assigned to after the estimation. As before, we assigned the data points to the clusters based on the maximum estimated probability of cluster membership. The sixth column shows the proportion of the time the data was classified into correct number of clusters across the replications. The table also displays the minimum and the average coverage across linear coefficients for each parameter set. For instance, the second line displays a case in which there are two latent clusters in the population and five covariates. The sixth column indicates that the data points were classified into two clusters in of the estimations performed using the data sets generated by that parameter set. There are 10 linear coefficients across clusters for that case (5 linear coefficients per cluster). Among those 10 linear coefficients, the minimum coverage probability was . It means that the linear parameter whose estimation had the worst coverage still was correctly estimated of the time. By correct estimation we mean the true value was within the 95% HPDI. So in at least cases, the true values were contained in the 95% HPD interval for all the linear parameters. One may argue that such good coverage probability occurs because the posterior intervals are too wide. So, we display in the last column of the table the maximum average of the HPD intervals among the linear coefficients in each case. As the intervals are generally small we can be confident that the model and the estimation procedure proposed here have good coverage probability and such results are not due to the large variance of the posterior distribution. Another possible objection is that the number of replications is too small. In the appendix we provide a much larger MC exercise for two additional parameter sets with replications each. The appendix also contains tables with the MC standard error for all simulations and for all linear parameter $\boldsymbol{\beta}$. The results are similar to those presented here.

Now we turn to a full example of an estimation with context-dependent latent heterogeneity. For this example, we used ten contexts ($J = 10$) and two covariates ($D_x = 2$). We

Table 1.3: Summary of the performance of the hdpGLM when estimating number of clusters (K) and linear coefficients (β) across 100 replications generated by 10 different parameter sets.

	Number of Clusters (K)					Coverage and HPD of linear coefficients (β)		
		Estimates across replications						
Number of Covariates	True	Mean	Minimum	Maximum	Correct (%)	Minimum.	Average	95% HPD (largest average)
0	1	1.05	1	2	95	99.05	99.05	(-0.49, 0.04)
5	2	2.04	2	3	96	90.00	93.20	(-7.74, -7.1)
2	3	3.15	3	4	85	95.00	97.66	(2.02, 4.05)
3	4	4.14	4	5	86	91.00	95.44	(-3.04, -1.09)
2	4	4.12	4	5	88	93.00	96.28	(-5.97, -4.30)
3	5	5.02	5	6	98	93.00	96.27	(7.69, 8.20)
4	7	7.07	7	9	95	91.59	96.54	(-3.69, -2.69)
5	7	7.08	7	8	92	92.00	96.30	(-2.87, -1.77)
3	10	10.11	10	12	91	93.00	96.54	(0.76, 3.34)
2	10	10.25	10	12	76	92.31	96.73	(-2.8, 2.03)

let the expectation of the effect β_1 of first covariate X_1 be a function of the context-level feature W_1, but the expectation of the linear effect β_2 of the second covariate X_2 is not a function of context-level features. In other words, we randomly sampled τ_{11} (the effect of W_1 on the expectation of β_1) from its prior distribution and set τ_{12} (the effect of W_1 on the expection of β_2) to zero. We set the number of clusters to two ($K = 2$). Figure 1.2 shows the result of the estimation. On the left panel of the figure we see the posterior distribution of the linear coefficients in each context. The vertical lines indicate the true values. We clearly see the posterior concentrated around the true values of the clusters. On the top-right of the figure, we see the estimated posterior averages for β_1 and β_2 for each cluster, in each context, as a function of the context feature W_1. We clearly see that the expectation of β_1 and the clusters are positive functions of W_1, but that is not the case for β_2. Finally, in the bottom-right we see the posterior expectation of τ. The estimated values are quite close to the true values and within a small 95% HPD interval.

To complete this section, we compared the predictive performance of the GLM and the hdpGLM in terms of RMSE for different numbers of latent clusters. We randomly generated 30 parameter sets, each one with the number of clusters ranging from 1 to 30. For each case, we generated 10 data sets and estimated both the GLM and the hdpGLM. The RMSE was computed in each case. The Figure 1.3 compares the predictive performance of the GLM and the hdpGLM. The value of the RMSE stays always low for the hdpGLM, as expected.

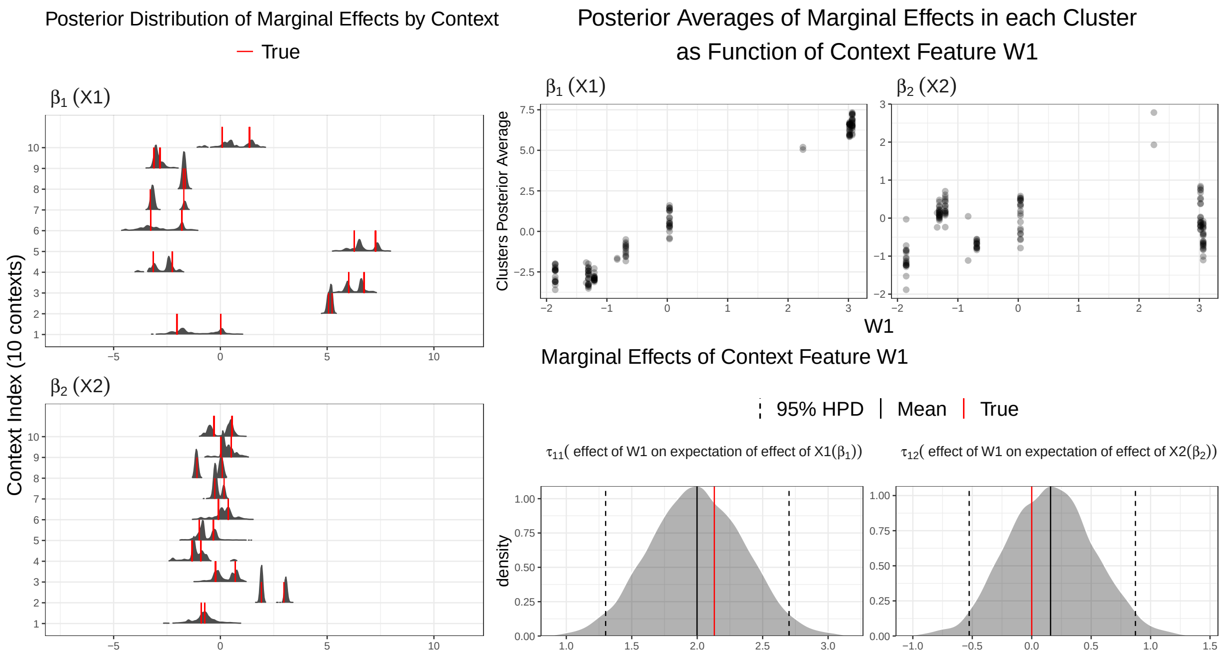


Figure 1.2: Output of estimation of hdpGLM model for a data set with 10 contexts and positive effect of context-level feature W_1 on the marginal effect β_1 of X_1

All estimation in this section and in the following we use $(\mu_{\tau_d}, \sigma_{\tau_d} I, \sigma_{\beta_{kj}} I, s^2, \nu, \alpha_0) = (0, 10I, 10I, 10, 10, 1)$ as prior parametrization, where I represents the identity matrix. Those values give a reasonably large variation for the underlying random variables and the simulation results have shown that they produce good coverage and small 95% HPD intervals in a large variety of situations. The appendix contains details of a prior perturbation study. Briefly, it shows that on average the model is not very sensitive to different prior settings, but in the worst case for certain combinations of prior parameters the model can demand very large data sets to escape the influence of the prior specification. This is true specially for extreme values of the concentration parameter α and values that produce highly dispersed inverse-scaled-χ^2 distribution, which can be generated by low values (below five) of the scale parameter s^2. For details, see appendix.

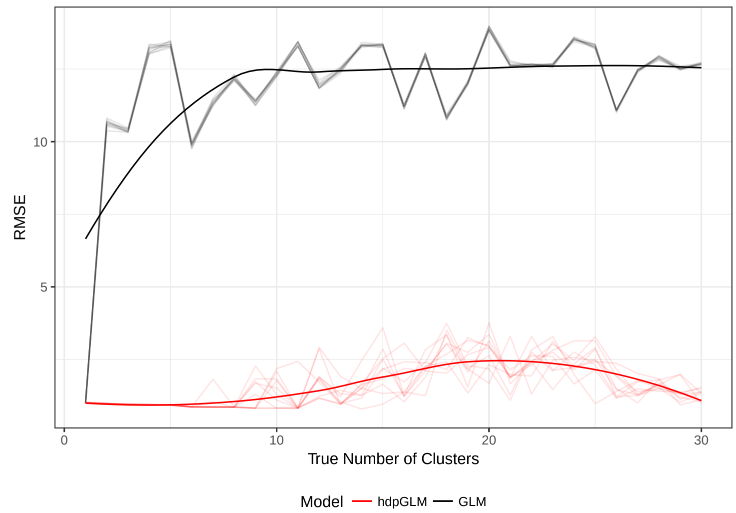


Figure 1.3: Comparing performance of hdpGLM and GLM using root-mean-squared error (RMSE) as a function of the number of clusters in the data.

1.6 Empirical Aplication

In this section, we illustrate some applications of the model by replicating empirical studies and comparing the original results with the ones produced by the hdpGLM estimates.

We start with Bechtel, Hainmueller and Margalit (2014), who present a study in Germany using online and telephone survey data. The paper investigates why some voters agree with bailout payments for other countries. The dependent variable is a dichotomous measure coded as 1 if the person is against bailout payments for over-indebted EU countries and 0 otherwise. They find that social dispositions, in particular feelings of cosmopolitanism and altruism, are the strongest predictors of attitudes toward providing financial help to other countries. The left panel of Figure 1.4 reproduces their results and displays the marginal effects of their three main variables. The right panel shows the estimation of the hdpGLM using an indicator variable for German states. The panel shows the effect of (very high) cosmopolitanism on support for bailout payments in each region. We see that for most of the states there is no latent heterogeneity. Moreover, the aggregate average effect estimated using a GLM is similar, for most cases, to the posterior average effect found by hdpGLM in each state. One exception is Lower Saxony, in which we see the Simpson's paradox: there are two clusters with opposite effects of very high cosmopolitanism on support for bailout. Although we would need further investigation to provide a substantive account of these results, we can see how the hdpGLM can be used to estimate context-dependent heterogeneity.

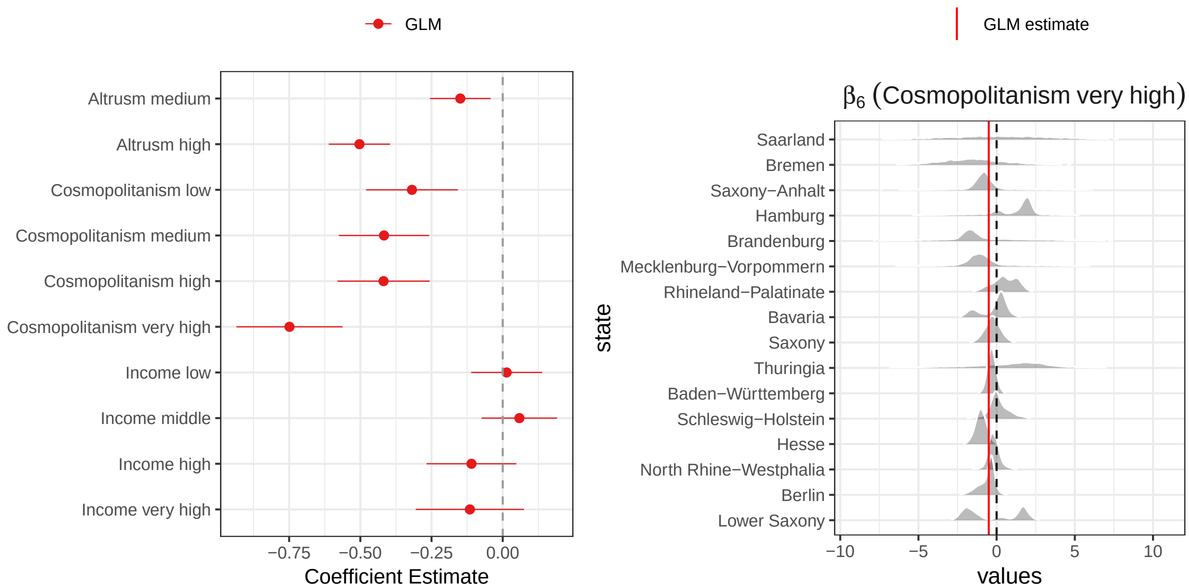


Figure 1.4: Left panel shows the effect of altruism, cosmopolitanism, and income on support for bailout estimated by GLM, reproducing Table 3 of Bechtel, Hainmueller and Margalit (2014). Right panel shows latent heterogeneity in the marginal effect of very high cosmopolitanism as function of German states.

For the second empirical application, we replicate Newman, Johnston and Lown (2015). Using national surveys conducted in the USA, they investigate if residential proximity to inequality affect US citizens' beliefs in meritocracy, defined as the idea that the economic system rewards individuals based on their hard work and ability. The data set contains individual- and county-level covariates. They show that the association between the individual's income and the probability of rejecting meritocracy is conditional on the levels of inequality in the county: low-income individuals become more likely to reject meritocracy when inequality increases. We reproduce their results for white residents, as they present in Table 1 of their paper, using a linear probability model. In their results, income and the percentage of blacks in the county do not matter alone, but the interaction between income and inequality is significant. We focus here on that result. We estimate the hdpGLM using the same individual- and county-level covariates they included in their model. County covariates are inequality, county income, percentage of black, percentage of votes for Bush in 2004, and county population. The estimation of the hdpGLM found no latent heterogeneity in 1633 out of 1688 counties. Two latent clusters were estimated in 54 counties, and

Table 1.4: GLM vs hdpGLM estimates for counties with no latent heterogeneity

Covariate	Parameter	GLM estimate	GLM Std Error	Average of posterior expectation across counties	Std Dev of posterior expectation across counties
(Intercept)	β_0	0.54	0.06	0.50	0.32
Income	β_1	-0.01	0.07	-0.08	0.33
educ_i	β_2	-0.10	0.02	-0.07	0.29
age_i	β_3	-0.00	0.00	0.00	0.01
gender_i	β_4	0.00	0.01	-0.00	0.19
unemp_i	β_5	0.01	0.01	0.02	0.22
union_i	β_6	0.02	0.01	0.06	0.20
partyid_i	β_7	-0.12	0.01	-0.13	0.24
ideo_i	β_8	-0.07	0.02	-0.06	0.29
attend_i	β_9	-0.03	0.01	-0.02	0.26

three latent clusters in one of them. Table 1.4 compares the MLE estimates of the GLM with the posterior expectation of the hdpGLM, averaged across counties with no latent heterogeneity. We can see in that table that those values are similar.

The left panel of Figure 1.5 shows the posterior distribution of the income effect in 20 randomly sampled counties. We see that the GLM and the hdpGLM estimates agree in many cases, but for some counties, there are latent heterogeneous groups and the estimates of the two models disagree. In the county with index 543, for instance, there are three latent groups, one in which the income plays no role, and two with opposite income effects. That case represents an example of the Simpson's paradox in the effect of income in that county.

As discussed, one of the advantages of using hdpGLM is that we can evaluate if there is any effect of context(county)-level variables after we take into account the latent heterogeneity in the effect of observed individual-level covariates. Newman, Johnston and Lown (2015) found that inequality conditions the effect of income on the probability of rejecting meritocracy. However, when we take into account the latent heterogeneity of the income effect in each county, that conditional effect disappers. It can be seen in Figure 1.5. In the top-right panel of the figure, we see the posterior expectation of each cluster within each one of the 1688 counties. In the bottom-right, we see the posterior distribution of τ_{11}, the effect of inequality on the expectation of the effect of income for each county and cluster. The results indicate that inequality does not change the effect of income when we consider latent heterogeneity in the effect of covariates.

As we can see, the hdpGLM model can be used to investigate latent heterogeneity in the effect of observed covariates in generalized linear models. When there is no heterogeneity, the results of GLM and hdpGLM are similar. When there is latent heterogeneity, the GLM can produce estimates that are incorrect for all or some subpopulations. By using

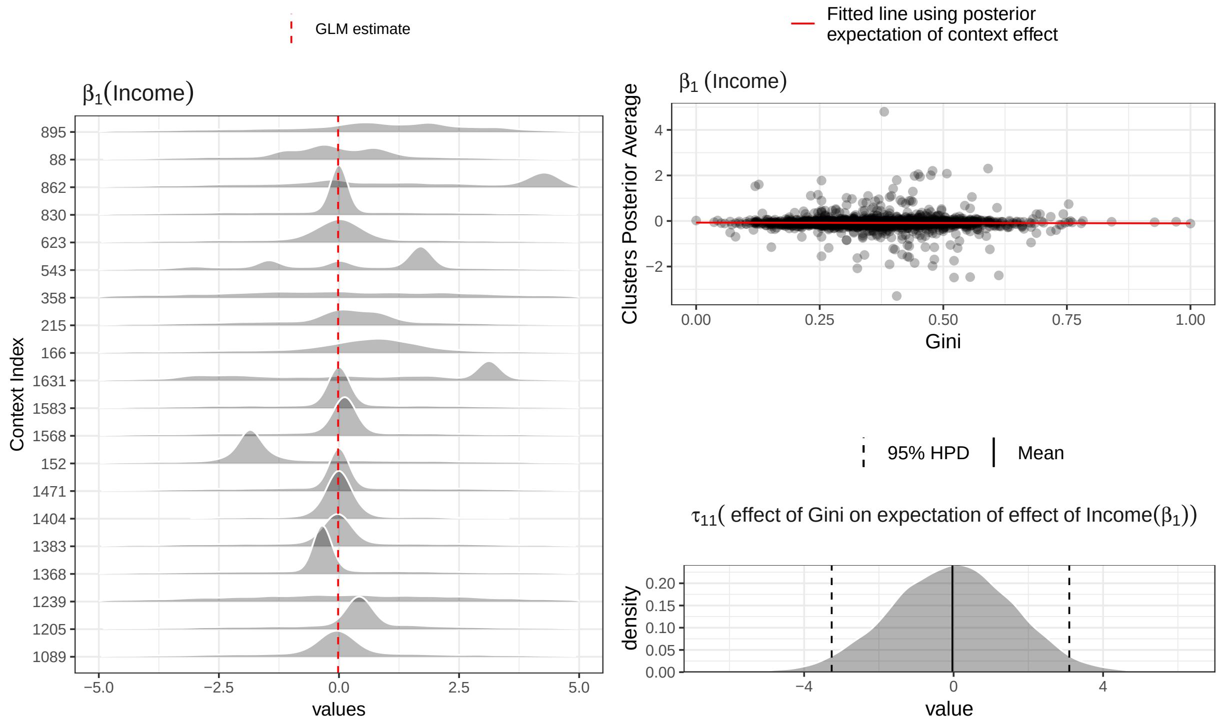


Figure 1.5: Posterior distribution of income effect for 20 selected counties (left panel), posterior expectation of income effect in each cluster as function of inequality (top-right panel), and posterior distribution of the effect of inequality on the income effect (bottom-right)

GLM, one is simply assuming that Simpson's paradox does not occur in the analysis. The hdpGLM can be used instead to estimate the heterogeneous effect, cluster the data into groups, uncover Simpson's paradox, and evaluate if the effect of context-level features remains relevant after latent heterogeneity is considered.

1.7 Final Discussion

Researchers in any academic discipline can never be sure *a priori* that there is no effect heterogeneity caused by latent or omitted variables in their investigation. In other words, we are never sure if there are latent subpopulations in which the average effect found using the aggregated data is different or even reversed. When there are such subpopulations, using GLM or GLMM can produce an incomplete picture and in the worst case scenario somewhat or completely misleading conclusion. This is true in analyses using either observational or experimental data. In either case, it is desirable to use a method that is robust to latent heterogeneity. Moreover, when data comes from different contexts, for instance, different states or different countries, it is common to assume that the effect of observed covariates varies from context to context due to context-level features. Likewise, it is also desirable to consider that the latent heterogeneity of the covariate effects within each context (e.g., country) can vary from context to context (from country to country) due to context-level features.

We have provided a model to address and uncover those issues empirically. The model is designed to estimate marginal effects in generalized linear models and consider if there are latent subpopulations in which the marginal effects differ. If data comes from different contexts, the model also estimates if the existence of such subpopulations and their specific marginal effects are functions of context-level features. We have shown that the proposed model causes no harm when the GLM is correct, that is, when there are no latent heterogeneous effects, but it correctly estimates the heterogeneous effects when they exist.

Similar to GLM, however, the proposed model requires specifying which and how observed covariates are included in the model. This is not a trivial task. It can affect the estimation as much as it does for GLMs. Further research is needed to develop methods to compare and select which observed covariates should be used and how. However, if for any reason one believes a specific set of covariates is adequate for a GLM, the proposed model can be used instead with the advantage that it will be robust to subpopulation heterogeneous effects.

CHAPTER 2

Polarization, Latent Heterogeneity, and the Determinants of Support for Redistribution

Abstract

Previous studies on the polarization of voters policy preferences only investigate polarization among observed socioeconomic groups (rich versus poor, white versus non-white), overlooking or ignoring within-group latent polarizations and cross-groups latent coalitions in policy preferences. This paper proposes a model to investigate latent polarization and latent coalitions of voters policy preferences. The model uses the hdpGLM approach to demonstrate how latent heterogeneity in the effect of observed covariates can lead to different latent structures of polarization in different political contexts. It presents an empirical illustration with ISSP data from OECD countries. The empirical example shows how one can use the model to investigate latent polarizations on support for redistribution within observed socioeconomic groups, or cross-class pro-redistributive coalitions in policy preferences.

2.1 Introduction

A prominent definition of polarization of policy preferences of voters approaches polarization as multimodality in the distribution of preferences across individuals and groups in the society (Fiorina, Abrams and Pope, 2008; Fiorina and Abrams, 2008, 2010). The multimodality means that the preferences of groups of people are clustered in different regions of the policy space. People that are closer or who occupy the same cluster have more similar policy preferences than people in different clusters. If the modes of the clusters are far apart and the variance around each mode is small, then one can conclude that polarization is higher than in alternative scenarios, i.e., cases with modes closer to one another or with large variance around the modes.

Although that concept of polarization of voters preferences is intuitive and informally used by many researchers, implicitly or not (Fiorina and Abrams, 2008), the current literature has't provided a framework to formalize that concept and study it properly. The closest approach to capturing that concept of polarization in redistributive preferences is proposed by Esteban and Ray (1994) (see also Esteban, Gradín and Ray (2007) and Esteban and Ray (2012)). The approach is limited because it is designed to quantify polarization by looking purely at the shape of the distribution of the outcome variable, e.g., the shape of the distribution of preferences for redistribution across individuals. It ignores an aspect that is crucial for political scientists: The preferences are associated with socioeconomic characteristics, which means that polarization occurs between social groups. Existing approaches that adopt the concept of polarization as multimodality in the distribution of preferences are limited in that regard. We propose an approach that extends the polarization model proposed in Esteban and Ray (1994) to account for socioeconomic determinants of policy preferences and the polarization between groups, and combines the extended model with the hdpGLM approach proposed in Ferrari (2019) to investigate latent polarization within observed socioeconomic groups or latent coalitions across those groups.

To illustrate the importance of the polarization model proposed here, we use survey data from the module Role of Government of the International Social Survey Programme (ISSP) from 1985 to 2016. The empirical example shows how the characterization of the polarization of preferences can drastically change if we consider policy preferences of the observed groups and the latent heterogeneity in the effect of observed covariates on those preferences. In France in 2006, for instance, the association between income and support for redistribution is different in three latent subpopulations. While it is negative for one latent group, it is positive for another, and close to zero for a third group. That latent heterogeneity in the effect of observed covariates is connected to multimodality in the distribution of preferences within income groups, but it also reduces distances in the preferences of individuals from different economic stratum. The French example illustrates how polarization can be incorrectly characterized if we ignore latent heterogeneities in the determinants of preferences.

The rest of the paper is organized as follows. The next section discusses studies of determinants of political preferences and the scholarship on the polarization of voters' preferences. Based on that discussion, it presents a model connecting those two streams of literature. It also presents our modeling approach to estimate latent polarization of policy preferences. Section 2.4 describes the data we use to illustrate the relevance of the model. That section is followed by the empirical analysis of polarization in OECD countries. Then, the conclusions summarize what we demonstrated in the previous sections: if polarization is understood as multimodality in the distribution of preferences, then we need an approach that is capable of (1) accounting for how that multimodality is conditional on observed socioeconomic groups and (2) how it is affected by latent heterogeneity in the behavior of those groups. That approach is what this paper proposes.

2.2 Theory and Characterization of the Problem

2.2.1 Polarization and the Determinants Political of Preferences

What is polarization of policy preferences, and how is it related to the studies of the determinants of those preferences?

The literature has explored the concept of polarization on different domains of political preferences (Fiorina and Abrams, 2008). We can identify at least four main groups or domains. The first is so-called *partisan polatization* (or party sorting). It refers to the number of people that self-identify with a particular party (Abramowitz and Saunders, 1998; Abramowitz and Jacobson, 2006; Abramowitz, 2010). The second has to do with *ideological polarization*, which refers to the self-identification of people as liberal, conservative, leftist, centrist, etc. Another is the *affective polarization*, which refers to the sentiments of people toward those that have different partisian, ideological, or policy preferences (Mason, 2015). Finally, a large literature has focused on *issue (or policy) polarization*, which refers to the polarization of opinions about various policy areas such as abortion, immigration, redistribution, government spending, etc. (DiMaggio, Evans and Bryson, 1996; Abramowitz and Saunders, 1998; Fiorina, Abrams and Pope, 2005; Abramowitz and Saunders, 2005; Baldassarri and Gelman, 2008; Fiorina, Abrams and Pope, 2008; Fiorina and Abrams, 2010; Mason, 2015; Kleiner, 2018; Mason, 2018). The discussion in this paper focus on that last domain, although it can be easily extended to studies that focus on the others.

Lets then consider *issue (or policy) polarization*. Authors have studied that concept of polarization from two main perspectives. Baldassarri and Gelman (2008), for instance, understand polarization as *issue constraint*, which refers to the extent to which opinions on different issues correlate, such that people that declare some preferences on some issues tend to declare some other specific preferences on other issues. One of the limitations in that approach is that often researchers study only pairwise correlations between different issues (Baldassarri and Gelman, 2008).

Various researchers have understood polarization as multimodality in the distribution of preferences (Fiorina and Abrams, 2008). In that definition, polarization is understood informally as "the intensification of opinion discrepancy dividing substantive parts of the society into opposing camps" of political preferences (Kleiner, 2018). From that perspective, that is, issue polarization as multimodality in the distribution of policy preferences, we can identify two major empirical approaches to study polarization. In the first view, polarization of public opinion is understood as an entrenchment of otherwise undifferentiated individuals in different poles of a political position scale (Esteban and Ray, 1994; Duclos, Esteban and Ray, 2004; Fiorina and Abrams, 2008, 2010). Researchers ignore the socioeconomic characteristics of the individuals and how it is related to policy positions and focus only on the shape of the distribution of the preferences. Public opinion may be view as polarized if, for instance, half of the population as a whole is strongly in favor of the anti-immigration policy, while the other half is strongly against that. This approach is used in Fiorina and Abrams (2008) to argue that there is little evidence of issue polarization in Americans' public opinion (see their Table 1, pg. 573).

Obviously, the problem with that approach is that there may be polarization between groups of people with particular characteristics (black versus white, poor versus rich), even though that polarization disappears in the pooled statistics (vide Simpson's Paradox (Simpson, 1951; Samuels, 1993; Hernán, Clayton and Keiding, 2011)). To illustrate that point, consider Figure 2.1. It shows the distribution of answers to the question "Do you think it should be the government's responsibility to provide a job for everyone that wants one?" (data from the ISSP collected in the USA in 2016). The left panel considers the entire population, and the right panel shows the distribution by income groups. There is little indication of polarization on the left panel because there is a single modal answer in the population. But the right panel shows that the modal response of the poor and the rich are located in different poles of the opinion scale, indicating polarization in public opinion between these groups.

The second view, more interesting and widely used in social research, considers that opinions are associated with individuals' socioeconomic characteristics and societies' institutional features (DiMaggio, Evans and Bryson, 1996; Baldassarri and Gelman, 2008; Fiorina and Abrams, 2008, 2010; Kleiner, 2018). That association connects studies of polarization with studies of determinants of political preferences. Polarization of public opinion is studied not as a conflict between generic individuals defined only by their po-

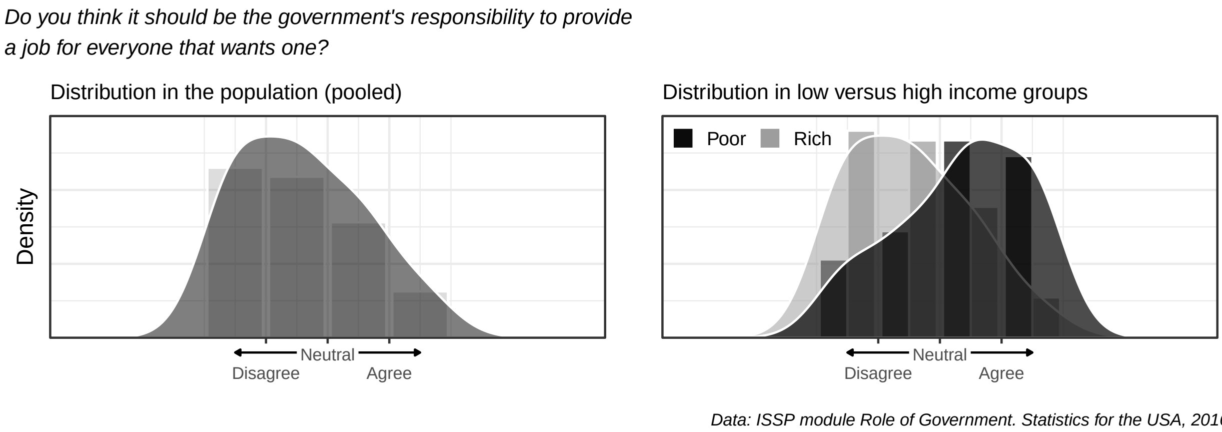


Figure 2.1: Comparing distribution of issue position using pooled data versus separated by income groups in the USA.

litical positions, but between groups or individuals that belong to certain socioeconomic groups and live in certain contexts. As long as opinions are associated with socioeconomic characteristics, the causes of polarization can be traced back to how socioeconomic features affect opinion, and polarization depends on that association.

The problem with that perspective is that researcher often mistakenly take the association between socioeconomic characteristics and preferences as if it were the polarization itself, ignoring the shape of the distribution of preferences that results from that association. For instance, in that second view, if there is a large negative effect of income on support for welfare policies, some may say that *issue polarization* emerges between the rich and the poor. If that negative effect increases, then one might conclude that the polarization also increases. Examples of that understanding can be found not only in the literature on *issue polarization* (DiMaggio, Evans and Bryson, 1996; Shapiro and Bloch-Elkon, 2006, 2007; Levendusky, 2009) but also on studies that focus on *partisian polarization* (Abramowitz and Saunders, 1998, 2005; Fiorina and Abrams, 2008), *ideological polarization* (Abramowitz and Saunders, 1998; DiMaggio, Evans and Bryson, 1996; Baldassarri and Gelman, 2008; McCarty, Poole and Rosenthal, 2016; Mason, 2018), and in statements about polarization in studies of the determinants of welfare policy attitudes (Beramendi and Rehm, 2016).

Equating polarization to the strength of the association between socioeconomic features and preferences can be misleading. Figure 2.2 illustrates that point. In that Figure, the x-axis represents a feature that is associated with a political position, represented in the y-axis, which can be partisanship, ideology, or policy preferences. The marginal distribution of the political position (y) is displayed in the right margin of each panel. All cases have the same association (β_x) between the socioeconomic feature (X) and the political position (y). However, in case 1 (left panel) the political positions are spread across the socioeconomic spectrum. Although there are people with extreme positions, the middle is populated, and the overall political polarization around y is not strong. In case 2 (central panel), the middle is empty and all individuals hold extreme political positions. In that case, despite the fact that the majority hold extreme political positions, the polarization is even smaller than case 1 because there is a large concentration of individuals with the same political position. In case 3 (right panel), on the other hand, the middle is empty and the society is more or less evenly distributed in the two poles. By the concept of polarization as multimodality as an entrenchement of relatively large groups in different poles of the position space, case 3 actually represents the most polarized of the three examples.

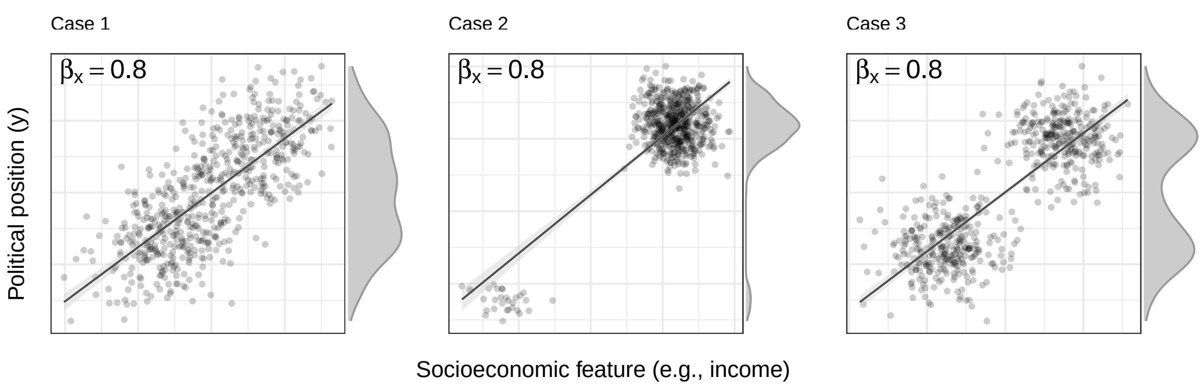


Figure 2.2: Three different examples of the underying distribution of political positions across individuals (right edge of each panel), but that have the same association β_x between socioeconomic characteristics (x-axis) and political positions (y-axis).

So, while the first view ignores the association of socioeconomic characteristics and preferences and only focuses on the shape of the distribution of the outcome variable (preferences), the second view focuses on the association between preferences and socioeconomic positions but ignores the results of that association on the shape of the preferences. As figures 2.1 and 2.2 show, the concept of polarization of public opinion as multimodality in the distribution of preferences and the studies of the determinants of those preferences are connected, but they are not the same object. Fiorina and Abrams (2008) seems to have a similar understanding that polarization and the association of socioeconomic features and preferences are not the same things. As they point out, although socioeconomic features are associated with political positions, ”contrasts in individual sociocultural characteristics are not direct indicators of political polarization." Their argument is that the strength of association changes over time and across features. They exhort that "[a]nalysts must provide additional information about the strength of the links between social characteristics and relevant political variables, as well as information about the stability of such linkages." In our understanding, as the examples above demonstrate, we should *not* treat polarization and the determinants of preferences as the same thing for yet another and more important reason. The concept of polarization refers not only to the strength of the association between socioeconomic characteristics and policy preferences, but also the density, i.e., the distribution or the relative size, of the groups with different preferences[1].

The take away of this section is the following. Some studies focus on the association between political positions and socioeconomic features (on the β's) to make statements about polarization. That understanding can result in misleading conclusions about polarization because a similar degree of association can occur along with very different underlying distributions of preferences, as illustrated in Figure2.2. Others focus on the distribution of the opinions and ignore how socioeconomic features and preferences are related. That can also be misleading because the shape of the distribution depends on taking into account that association, as shown by Figure 2.1. To properly measure and analyze polarization as multimodality, we need to combine those two perspectives. We provide that unified framework in section 2.2.3. Before introducing our approach, to develop fully the model, we need to discuss a related problem, which refers to latent heterogeneity in the association between observed covariates and preferences, which can hide latent polarization in policy preferences. The next section explores that problem.

2.2.2 Latent Heterogeneity in the Determinants of Preferences and Polarization of Public Opinion

The connection between the determinants of preferences and preference polarization raises a fundamental problem for empirical analysis. To characterize polarization, we need to correctly characterize how observed features are associated with policy preferences (Fiorina and Abrams, 2008). Figure 2.3 illustrates the problem. In that picture, the straight lines represent the average association between income and support for redistribution. Let's

[1]That understanding of polarization between socioeconomic groups and the density of the diverging groups is implicitly or explicitly on the basis of the theoretical concerns about consequences of polarization to various political outcome such as to social stability, regime survival, party fragmentation, party ideological differentiation, policy outcomes and so on (Downs, 1957; Boix, 2003; Acemoglu and Robinson, 2006; Brooks and Manza, 2006*b*,*a*, 2008; Ansell and Samuels, 2010).

assume that the population is concentrated in the circled regions. The left panel displays a case in which income and support for redistribution are negatively associated. If that association is negative and unconditional on other factors, scholars would promptly conclude that there is a public opinion polarization between the rich and the poor (see for instance Fiorina and Abrams (2008) and Kleiner (2018)). If, however, the effect of income is different for different latent subpopulations, such that income is associated with more support for redistribution among individuals in one group, but with less support among individuals of another latent group, then the picture of polarization of opinion would be completely different. This is depicted in the right panel of Figure 2.3. Each line represents the average association between income and support for redistribution in the two groups. Poor individuals of one group would hold attitudes that are more similar to rich people rather than poor people in the other group, opening the possibility of intra-class polarization and cross-class coalition.

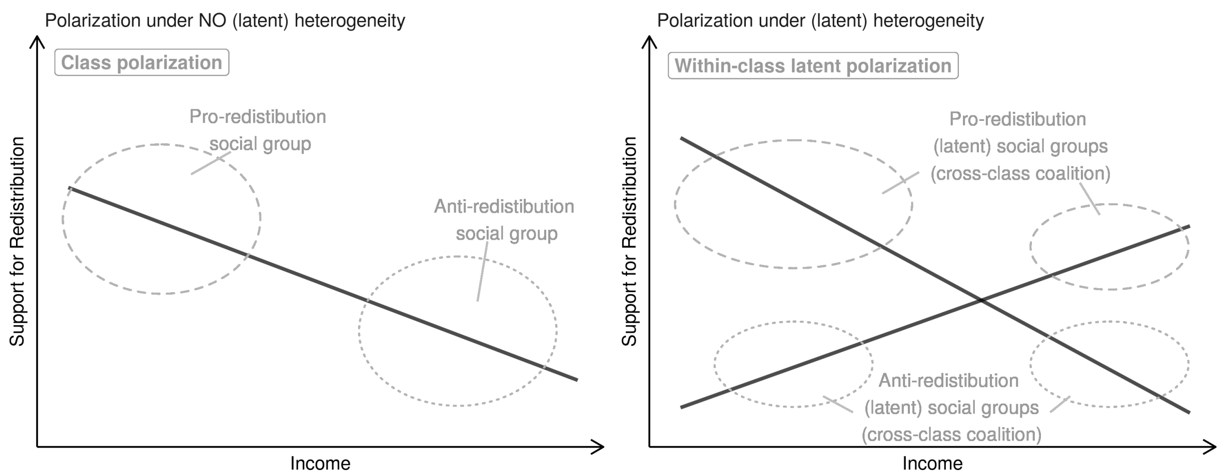


Figure 2.3: Polarization of policy preferences with (right) and without (left) latent heterogeneity in the association between income and support for redistribution.

All empirical work that investigates the association between characteristics of people and their political position have used classical GLM or mixed effects models to estimate that association, which assumes a situation analogous to the one depicted in the left panel of Figure 2.3 (DiMaggio, Evans and Bryson, 1996; Layman and Carsey, 2002; Fiorina, Abrams and Pope, 2005; Fiorina and Abrams, 2008; Baldassarri and Gelman, 2008; Fiorina and Abrams, 2010). Those approaches require the assumption that there are no latent or unobserved features that condition the effect of observed covariates. Conclusions about the polarization of public opinion are based on that underlying assumption. As the right panel of the Figure 2.3 shows, if that assumption is incorrect and there is (latent) heterogeneity in the effect of any observed feature, then that can completely change our understanding of which groups hold polarized political views polarized from each other. It is desirable to have a method that is more flexible and relaxes that assumption of no effect heterogeneity. Below, we discuss why such latent heterogeneity would emerge in the particular empirical application we use in this paper to illustrate our approach, but before that, the next section presents our model of polarization that accounts for the issues discussed so far.

2.2.3 A Unified Framework of Policy Preference Polarization and Determinants of Policy Preferences

This section formalizes the discussion presented in the sections 2.2.1 and 2.2.2. To do that, we extend the model of polarization proposed by Duclos, Esteban and Ray (2004) to (1) incorporate the idea that preferences are a function of socioeconomic features, (2) evaluate polarization between social groups, not only the aggregate polarization in the society, and (3) account for the latent heterogeneity in the conditional effect of observed covariates and the implications of that heterogeneity to characterize the polarization among social groups. A toy example is discussed to illustrate the development of formal analysis.

Esteban and Ray (1994) and Duclos, Esteban and Ray (2004) propose an *alienation-identification* framework to measure polarization. Their model is defined as follows. Let y denote a value representing a political position and $f(y)$ its density *across individuals.* The degree of *alienation* that individual i feels in relation to another individual j is given by (see also Sen et al. (1997))

$$\delta_i = \left| y_i - y_j \right|$$

Esteban and Ray (1994) define *effective antagonism* between i and j as a function $T(f(y_i), \delta_i)$ with the following properties: $T \in [0, \infty)$, $\dfrac{dT}{d\delta_i} > 0$ and $T(f, 0) = T(0, \delta_i) = 0$. In words, the *effective antagonism* between individuals can be null or positive ($T \in [0, \infty)$), it increases with the degree of alienation between their preference ($\dfrac{dT}{d\delta_i} > 0$), and it is null if either their preferences are identical ($T(f, 0) = 0$) or one of them hold a completedly isolated opinion not shared by anyone else in the near neighbourhood[2] ($T(0, \delta_i) = 0$).

[2]This last element means that effective antagonism is a social concept by definition, as it depends on the density of people holding (dis)similar views. For details and discussions about that neighbourhood, see Duclos, Esteban and Ray (2004) and Esteban and Ray (1994).

Duclos, Esteban and Ray (2004) defines polarization as an accumulation of effective antagonism in the society, that is, as a measure defined on T and f as follows:

$$P(f) \triangleq \iint T(f,\delta_i)dF(y_i)dF(y_j) \tag{2.1}$$

The authors show that $P(f)$ satisfies some desirable properties that match common intuitive understanding of polarization if $T(f,\delta_i) = |y_i - y_j| f(y_i)^{\alpha}$ and $\alpha \in [0.25, 1]$ (for details see Duclos, Esteban and Ray (2004)). Note that if $\alpha = 1$, equation (2.1) is just the iterated expectation of the L_1-distance.

To illustrate those properties, consider Figure 2.4. The Figure contains six hypothetical scenarios and their respective measure of polarization. The top-right panel (panel A) represents a unimodal distribution of preferences. Below that panel, we see a bimodal distribution (panel B.1), followed by a case with the exact same modes, but with preferences compressed around them (panel B.2). We see that $P(f)$ captures our intuition about which one of those cases represent a more polarized society. The right column of the figure continues the example with a distribution with four modes. The polarization increases if the distribution becomes more concentrated around the modes, and even more if, additionally, the central-left and central-right positions go extreme.

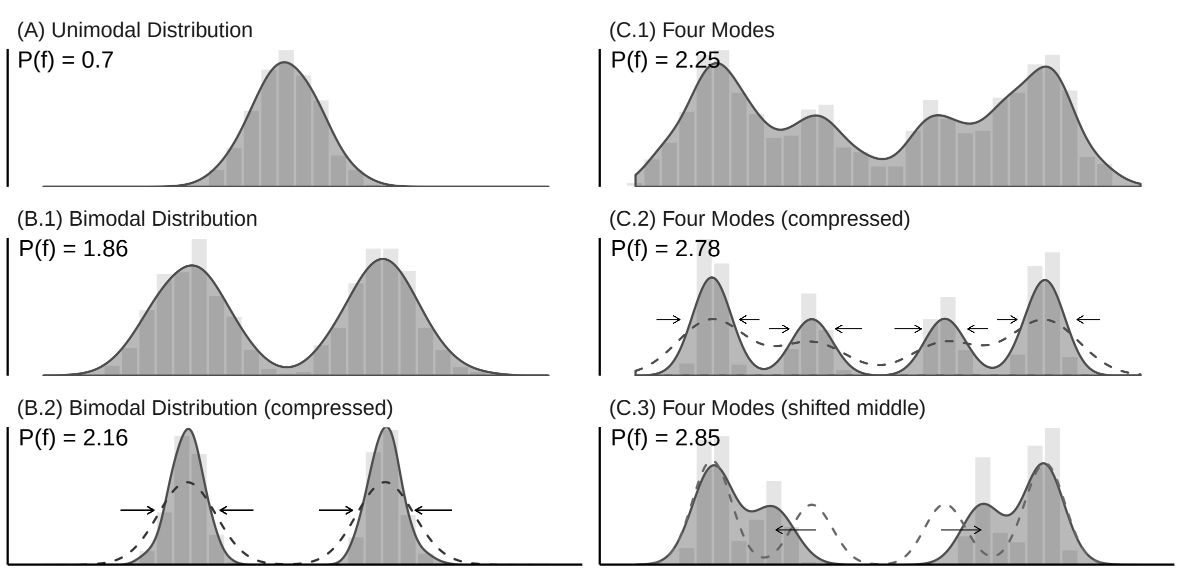


Figure 2.4: Illustrative examples of the polarization measure $P(f)$ under different polarization scenarios.

Note that that definition lacks any notion that the policy preference (y_i) depends on individual's socioeconomic characteristics (X_i). Under that formulation, it is impossible to evaluate how social groups are polarized on an issue because individuals are characterized exclusively by their policy preference position (y_i). We can only measure alienation of i with respect to another individual j (measured by δ_i), the effective antagonism ($T(f(y_i),\delta_i)$), and the aggregate polarization in the society ($P(f)$). We would like to be able to measure the strength of the association between preferences and socioeconomic characteristics, as well as the polarization between social groups, let's say between education or income groups, as stressed by Fiorina and Abrams (2008). In order to do that, I extend their model in the following way.

Let X_i denote socioeconomic characteristics of individual i. As before, let $y \sim f(y \mid X_i, \theta)$ denote the distribution *across individuals*. We follow the most common empirical approach and define the observed policy preferences y_i of individual i as a linear function of X_i and some individual-specific mean-zero random disturbance ε_i.

$$y_i = X_i^T \beta + \varepsilon_i \tag{2.2}$$

With that definition, we not only redefine the *alienation* and *effective antagonism* as functions of socioeconomic features that affect preferences, but also as functions of β, which quantifies how the socioeconomic feature X is associated with political preference y. In particular, we define $\delta()$ as the module of the different between the expected values of y_i and y_j, which gives:

$$\delta(X_i, \beta) = \left|\mathbb{E}[y_i] - \mathbb{E}[y_j]\right| = \left|X_i^T \beta - X_j^T \beta\right| \tag{2.3}$$

If we assume that the effect of X is homogeneous in the population, as defined by equation (2.2), that is, that socioeconomic characteristics of individuals and their political preferences are associated in the same way for everyone in the society, we can easy evaluate how socioeconomic features affect antagonism. For simplicity, assume $X_i = (1, \mathbb{R})^T$ and $\beta = (\beta_0, \beta_1)^T$. We have:

$$\frac{d\delta_i}{dX_j} = -\frac{(X_i - X_j)}{|X_i - X_j|} |\beta_1| \tag{2.4}$$

Because by definition $\frac{dT}{d\delta} > 0$, we have

$$\delta(X_i, X_j) > \delta(X_i, X_j') \implies T(f, \delta_i) > T(f, \delta_i') \tag{2.5}$$

Although the effect on the overall polarization in the society ($P(f)$) depends on $f(y \mid X, \theta)$, by equations (2.4) and (2.5) is easy to see when antagonism increases with the distance between the socioeconomic characteristics of individuals i and j:

$$\begin{cases} X_i > X_j & \implies \frac{d\delta_i}{dX_j} < 0 \\ X_i < X_j & \implies \frac{d\delta_i}{dX_j} > 0 \end{cases} \tag{2.6}$$

This simple extension allows us to tackle the first two problems pointed in the first paragraph: (1) It incorporates the idea that preferences are a function of socioeconomic features in the analysis of polarization, and (2) it allows us to evaluate polarization between social groups by holding X_i at specific values.

To use a toy example, suppose that X denotes income and y the preference for redistribution. If the income of individual i is bigger (smaller) than the income of another individual j, then alienation and effective antagonism will diminish (increase) if the poorer (richer) individual j gets richer. The changes depend on wealth (X_i) and they are proportional to how much wealth affects the attitudes toward redistribution (β_1). The magnitude of the effect of income matters, but its direction doesn't. That is, given X_i and X_j the conclusion about antagonism is the same, but it doesn't matter if the effect of income is negative or positive.

Now suppose that the assumption about the homogeneity of the effect of socioeconomic characteristics on preferences embedded in equation (2.2) does not hold, but instead that some people belong to different groups that differ in terms of how their socioeconomic features affect their political attitudes. For instance, suppose that income does not have the same effect on preferences for everyone. While for some people more income leads to less support for redistribution, for others income leads to more support, perhaps because of their different views about whether economic success is a result of effort. Denote β_k and β_l the effect of income for those two different groups. If i belong to group k and j belongs to group l, then:

$$\begin{aligned} y_i &= X_i^T \beta_k + \varepsilon \\ y_j &= X_j^T \beta_l + \varepsilon \end{aligned} \tag{2.7}$$

Under such a heterogeneity, it is not as straighforward as before to infer how a change in the distance between socioeconomic characteristics of individuals i and j affect their alienation, antagonism, and the overall polarization. Now, it depends on the socioeconomic features, the effect of features on preferences, and the group that the individuals belong. Now, we need to know the latter information. Again, for simplicity, assume $X_i = (1, \mathbb{R})^T$, $\beta_g = (\beta_{0g}, \beta_{1g})$, and $g \in \{k, l\}$. We have:

$$\frac{d\delta_i}{dX_j} = -\left[\frac{(\beta_{0k} - \beta_{1l}) + (X_i \beta_k - X_j \beta_l)}{\left|(\beta_{0k} - \beta_{1l}) + (X_i \beta_k - X_j \beta_l)\right|} \right] \beta_{1l} \tag{2.8}$$

and

$$\begin{aligned} \beta_l > 0 &: \begin{cases} \dfrac{d\delta_i}{dX_j} < 0 \iff X_i^T \beta_k > X_j^T \beta_l \\ \dfrac{d\delta_i}{dX_j} > 0 \iff X_i^T \beta_k < X_j^T \beta_l \end{cases} \\ \beta_l < 0 &: \begin{cases} \dfrac{d\delta_i}{dX_j} < 0 \iff X_i^T \beta_k < X_j^T \beta_l \\ \dfrac{d\delta_i}{dX_j} > 0 \iff X_i^T \beta_k > X_j^T \beta_l \end{cases} \end{aligned} \tag{2.9}$$

To continue the toy example, if the income of two individuals i and j becomes more similar, neither do their preferences necessarily converge nor does the aggregate polarization diminishes. Antagonism and polarization may diminish depending on how income affects preferences for each group of individuals k and l, as depicted in the Figure 2.3. In that example, in which $\beta_k = a\beta_l, a < 0, \beta_k, \beta_l > 0$, the alienation between policy preferences of a poor individual i in one group and another poorer individual j in another group diminishes if the latter gets richer, but the preference alienation between j and another individual j' from the same group l of j increases. The effect on the overall polarization is not as straightforward to predict because it depends on the density $f(y)$, but we clearly see that alienation and social antagonism are deeply affected by hetegoeneous effects.

This extension allows us to tackle the last problem pointed above, that is, accounting for heterogeneity in the conditional association between the observed covariates and the outcome, and the implication of such heterogeneity to characterize polarization among social groups. In the typical situation, the researcher is unsure about the existence of that heterogeneity in the conditional association between X and y. With the formulation of polarization presented here, however, it is easy to use empirical models to estimate the heterogeneous effects of the linear coefficients, as we show in the empirical analysis. The next section motivates our working example. The empirical strategy to estimate polarization and account for latent heterogeneity is presented in the sequel.

2.3 Empirical Application: Polarization of Preferences for Redistribution in OECD countries

To restate the main motivation of the model of polarization presented in the previous section, the goal is to (1) estimate polarization as a function of socioeconomic determinants of political preferences and (2) investigate latent polarization caused by latent heterogeneity in the association of observed socioeconomic features and preferences. We illustrate how the model achieves those goals with an application that investigates polarization in redistributive preferences in OECD countries. This section motivates the empirical application.

In recent years, the literature on the determinants of redistributive preferences grew substantially. The sociology literature has emphasized that social classes, i.e., occupation groups, differ in their redistributive preferences, especially in countries with large welfare states, because redistribution and welfare state spendings have a *decommodification* effect on the lower classes and increase their power in the job-market negotiations (Esping-Andersen, 1990; Blekesaune and Quadagno, 2003; Edlund and Lindh, 2015; Fernández and Jaime-Castillo, 2017; Jaime-Castillo and Marqués-Perales, 2018).

The political science literature has paid more attention to other factors, in particular the economic status (income), market risk, values, and identity (Cusack, Iversen and Rehm, 2006; Fehr and Schmidt, 2006; Fowler and Kam, 2007; Rehm, 2009; Beramendi and Rehm, 2011; Costa-Font and Cowell, 2015; Rueda, 2018).

In this study, we will focus on the effect of income for many reasons. First, among those factors, income has a privileged position. The economic status of individuals is certainly an omnipresent feature in studies about attitudes toward welfare policies. Virtually all empirical studies investigating determinants for redistribution, even when arguing that other factors matter, take that into account[3]. Although there is a cross-country variation in the magnitude of the effect of income, a negative association is consistently found in many countries (Beramendi and Rehm, 2016). Second, as already discussed, many important theories in political science about revolution, social stability, survival and emergence of democracy, policy outcomes, the size of the government, etc., not only implicitly assumes polarization of redistributive preferences, but also that it occurs along income lines (Downs, 1957; Meltzer and Richard, 1981; Boix, 2003; Acemoglu and Robinson, 2006; Ansell and Samuels, 2010; Alesina and Giuliano, 2010). Third, studies about polarization in the USA have shown that income status is an important element affecting various types of political positions associated with polarized attitudes (Stonecash, 2005; Fiorina and Abrams, 2008; Baldassarri and Gelman, 2008; Lelkes, 2016). Finally, no existing studies have to our knowledge evaluated polarization of redistributive attitudes between income groups after taking into account their considerations presented in the previous sections about the relationship between determinants of preferences and its distribution, or the potential consequences of latent heterogeneity in the effect of that important variable on the conclusions about polarization.

But why would there be latent heterogeneity in the effect of income? Among some reasons presented by the literature, the support for welfare policies among the rich can be conditional on their beliefs about how redistribution helps to mitigate crime (Rueda and Stegmueller, 2016). Moreover, authors have argued that association between income and support for redistribution can be conditional on feelings of marginalization because "disadvantaged groups likely face significant obstacles to achieving political influence and

[3]The list is endless. See Bean and Papadakis (1998); Bowles, Gintis et al. (2000); Fong (2001); Huber and Stephens (2001); Alesina and La Ferrara (2005); Alesina and Angeletos (2005); Gilens (2005); Carsey and Layman (2006); Lubker (2006); Larsen (2008); Finseraas (2008); Rehm (2009); Chen and Li (2009); Jaeger (2009); Alesina and Giuliano (2010); Dallinger (2010); Baldwin and Huber (2010); Lupu and Pontusson (2011); Blofield and Luna (2011); Rehm, Hacker and Schlesinger (2012); Bechtel, Hainmueller and Margalit (2014); Bellani and Scervini (2015); Costa-Font and Cowell (2015); Kuziemko et al. (2015); Rueda and Stegmueller (2016); Beramendi and Rehm (2016); Morgan and Kelly (2017); Walter (2017); Ballard-Rosa, Martin and Scheve (2017); Rueda (2018); Compton and Lipsmeyer (2019) and references therein.

rarely attain substantial material gains through state redistribution", which makes people in those groups to stop believing that the state can take any action that benefits them (Morgan and Kelly, 2017). Another possible reason has to do with perceptions about the beneficiaries. If they are perceived as in(out)-group members, the negative effect of income can be mitigated (intensified) (Luttmer, 2001; Alesina and Glaeser, 2004; Gilens, 2009). Another reason could be the perceptions about whether effort and hard work are rewarded with economic success, which can condition the effect of income depending on unobserved individuals' experiences in the job-market (**?**Alesina and Angeletos, 2005). In any case, the assumption of homogeneity in the average association between preferences and socioeconomic features is just that: an assumption. There might be factors currently unimagined by researchers that condition the effect of observed covariates. As discussed earlier, we need to account for those cases and relax the assumption of homogeneity to properly characterize polarization.

2.4 Data and Research Design

Our empirical analyses use the module *Role of Government* of the ISSP data collected in 1985, 1990, 1996, 2006, and 2016. Table 2.1 in the next section contains a list of countries in each year included here. The main dependent variable, *Preferences for redistribution*, is measured by the survey question "On the whole, do you think it should be or should not be the government's responsibility to reduce income differences between the rich and poor?", measured in a 4 points scale. We select that question because it has become the standard question in the political economy literature to study support for redistribution (Lubker, 2006; Jæger, 2006; Kenworthy and McCall, 2008; Rehm, 2009; Finseraas, 2009; Dion and Birchfield, 2010; Rueda and Stegmueller, 2016; Beramendi and Rehm, 2016; Fernández and Jaime-Castillo, 2017; Rueda, 2018).

We use deciles of the standardized version of total household income divided by the number of households as our income measure. The ISSP measures income in different countries and years in different ways. In some cases, income data is available only in categories. When that is the case, we use the median of the category as the measure of income and compute the deciles using those values. That approach allows a straightforward comparability and standardization of income groups in terms of their relative position in the income distribution in their country (for similar procedures, see Rehm (2009); Rehm, Hacker and Schlesinger (2012)).

Following the literature, we include as control age (in years), education (in 3 categories), sex, employment status (coded 1 if employed, and 0 otherwise), and social class. The latter is measured in six categories based on the Erikson-Goldthorpe-Portocarero (EGP) scheme, in which we aggregate Service class I and II and Manual supervisors/Lower grade technicians and Skilled workers (classes V and VI) (Finseraas, 2009; Edlund and Lindh, 2015; Fernández and Jaime-Castillo, 2017; Rueda, 2018). We also estimate a parsimonious model with only age, education, and sex as controls to maximize the number of countries and years included in the analyses. The results presented in the paper are based on the parsimonious model.

To compare the estimates of polarization with and without the assumption of effect heterogeneity, we adopt the following strategy. First, we estimate GLM's in each country and year using preferences for redistribution as the dependent variable, which assumes homogeneity in the effect of the observed covariates. Then, we adopt the hdpGLM model presented in Ferrari (2019) to relax that assumption and estimate the country- and year-specific latent heterogeneity in the effect of observed covariates on preferences for redistribution. The two sets of linear predictors estimated by these two models are used to compute $\hat{y}_i$, the fitted value of support for redistribution of individual i (estimated posterior expectations are used for the hdpGLM estimates).

Let $m \in \{\text{het}, \text{nohet}\}$ indicate values computed under assumption of no heterogeneity (nohet, using GLM) and values after relaxing that assumption (het, using hdpGLM). Using a gaussian kernel to estimate $\hat{f}$ (Duclos, Esteban and Ray, 2004) , we estimate $\hat{\delta}_i^m$ and $\hat{P}^m(\hat{f})$, which are the estimators of alienation and polarization, respectively, with (see Duclos, Esteban and Ray (2004) and Appendix B.1 for details):

$$\begin{aligned} \hat{\delta}_i^m(X_i, X_j) &= |\hat{y}_i - \hat{y}_i| \\ \hat{P}^m(\hat{f}) &= \frac{1}{n}\sum_{i=1}^{n} \hat{f}(\hat{y}_i)^{\alpha}\hat{a}(\hat{y}_i) \end{aligned} \tag{2.10}$$

where,

$$\hat{a}(\hat{y}_i) = \hat{\mu} + \hat{y}_i \left(\frac{1}{n}(2i-1) - 1 \right) - \frac{1}{n} \left(2 \sum_{j=1}^{i-1} \hat{y}_j + \hat{y}_i \right)$$

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} \hat{y}_i$$

These estimates will provide information about how socioeconomic characteristics are associated with preferences for redistribution and polarization of public opinion. We are interested in (1) how information about the association between the covariates, particularly income in our ilustration, and support for redistribution can change our conclusions about polarization of redistributive preferences, and (2) how latent heterogeneity in the association between the covariates and preferences affect our characterization of polarization between observed socioeconomic groups. In the later case, we want to know how uncovering latent heterogeneity reveals produces latent polarization among observed socioeconomic groups. Formally, we should expect to have $\hat{P}(\hat{f}, \hat{\delta}) \neq \hat{P}(\hat{f}, \hat{\delta}(X, \hat{\beta}))$. Moreover, $\hat{\delta}_i^{\text{het}} = \hat{\delta}_i^{\text{nohet}}$ and $\hat{P}^{\text{het}}(\hat{f}) = \hat{P}^{\text{nohet}}(\hat{f})$ if and only if the assumption of homogeneity of the effect of covariates on support for redistribution among observed socioeconomic groups holds. Otherwise, latent heterogeneity should provide very different characterization of antagonism between social groups and the polarization in the society.

2.5 Empirical Analysis

2.5.1 Latent Heterogeneity in the determinants of Redistributive Attitudes in OECD Countries

The first step of our empirical analysis is to investigate the association between observed covariates and support for redistribution and see if there is any indication of latent heterogeneity in that association.

Table 2.1 displays the estimated number of clusters in each country and year. The dashes indicate that data is unavailable for that country-year. Cases with more than one cluster mean that there are subpopulations in which the observed covariates trigger different political attitudes. The table shows two things. First, almost half of the cases (51.5%, 34 out of 66) display some latent heterogeneity. Second, the number of clusters is relatively stable across years for each country. The USA, for instance, does not show latent hetero-

Table 2.1: Number of (latent) clusters estimated using hdpGLM model in each country and year using ISSP, module Role of Government

	Number of Clusters						Number of clusters				
Country	1985	1990	1996	2006	2016	Country	1985	1990	1996	2006	2016
Australia	1	4	–	1	1	New Zealand	–	–	1	1	2
Canada	–	–	1	1	–	Norway	–	1	1	2	3
Czechia	–	–	1	1	–	Philippines	–	–	–	2	2
France	–	–	2	1	3	Poland	–	–	3	3	–
Germany	–	4	4	2	3	Russia	–	–	2	3	3
Hungary	–	2	3	2	3	Slovenia	–	–	2	2	3
Ireland	–	2	2	1	–	Spain	–	–	–	3	3
Israel	–	1	–	2	3	Sweden	–	–	1	1	1
Japan	–	–	1	1	1	Switzerland	–	–	4	1	1
Latvia	–	–	2	1	3	UK	1	2	1	1	1
–	–	–	–	–	–	USA	1	1	1	1	1

geneity in any year since 1985. There are no latent socioeconomic groups whose observed characteristics have a noticeably different effect on preferences for redistribution. The same goes for Japan, Canada, and a few other countries. Various European countries, on the contrary, have latent subpopulations whose observed characteristics *do* have a noticeably different effect on preferences for redistribution.

Let's consider the association between income and support for redistribution. How does the estimation of that association differ when latent heterogeneity is taken into account? How does that affect our characterization of the polarization in the countries?

To answer the first question, consider Figure 2.5, which illustrates the estimated linear association between income and support for redistribution using data from 2006. The x-axis displays the posterior average of the income effect estimated by the hdpGLM approach, which relaxes the assumption of no latent heterogeneity. The y-axis shows the estimates produced by classical GLM, which assumes no latent heterogeneity. All cases that show no latent heterogeneity (the USA, Canada, Japan, etc.) lie on the 45^o dotted line, which represents cases whose estimated values are the same assuming no latent heterogeneity or not. However, for all other cases, in this application, the assumption of homogeneity in the effect of income overestimate the magnitude of the negative association. In cases like Norway, there is a latent subpopulation in which the income has no effect on its redistributive attitude, while for another subpopulation the effect is negative.

To see these results in more detail, consider Figure 2.6. It shows the variance of the

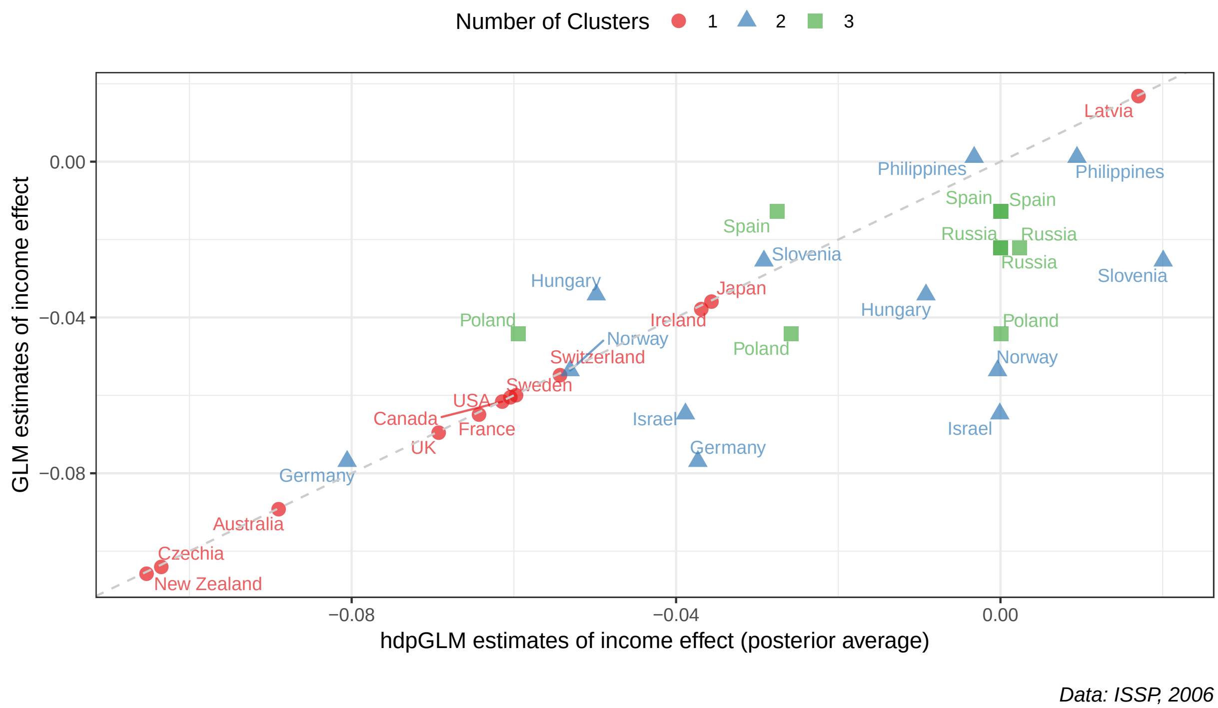


Figure 2.5: Comparing income slopes estimated using GLM and hdpGLM

conditional association between income and support for redistribution across countries. The left panel displays the results under the assumption of homogeneity. The right panel shows the estimates after relaxing that assumption. In the right panel, the percentage of the sample classified in each cluster is displayed next to the country's name. When the observations fit into a single cluster, no percentages are shown. For the case of Norway mentioned earlier, the income plays no role in the attitudes toward redistribution for 41% of the individuals sampled. The Figure shows that if we take latent heterogeneity into account, there is much more cross-country variation in the association between income and support for redistribution than if latent heterogeneity is assumed away.

Figure 2.7 shows the results for all survey years in four countries, France, Japan, New Zealand, and the USA. The Figure shows the estimated association between income and support for redistribution ($\hat{\beta}_{\text{income}}$). The GLM estimates, which assumes no latent heterogeneity, are displayed in vertical lines. The Figure also shows the posterior densities estimated by the hdpGLM, which takes into account latent heterogeneity in the association of income and support for redistribution. The number of clusters estimated in each year is at the top-left corner of each panel. In the USA and Japan, two cases with no estimated

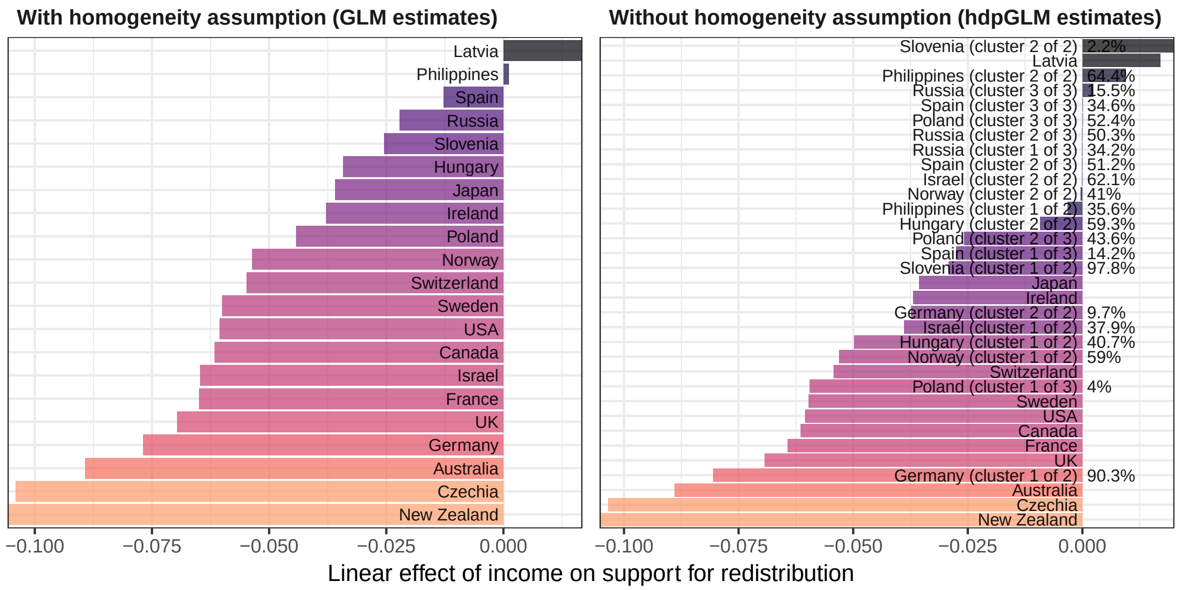


Figure 2.6: Marginal effect of income on support for redistribution in different countries. Left panel contains GLM estimates. Right panel contains hdpGLM estimates with cluster-specific linear effects between parenthesis. The percentage of the population in each cluster is displayed next to the country's name. Countries without that information are those in which all population belongs to the same cluster (homogeneity in the effect of income). *Data: ISSP 2006.*

latent heterogeneity in any year, the densities are centered at the value estimated under no heterogeneity assumption, as expected. For New Zealand, we see a movement toward zero since 1996. That is, the magnitude of the total effect of income started diminishing in that country. In 2016, the population diverged, and while for a subpopulation income was still negatively associated with redistributive attitudes, for another latent group the movement toward zero continued. France is another interesting case. Assuming homogeneous behavior within income groups, one would conclude that income is negatively associated with support for redistribution. However, when we take into account heterogeneity in the behavior of observed income groups, in 2016 emerges a subpopulation in France in which income is *positively* associated with redistributive attitudes.

The take away of the analysis in this section is the following. Using the exact same linear covariates, we see that there is latent heterogeneity on their effect on support for redistribution in some OECD countries but not in others. Selecting income as the working variable to ilustrate our point, in some countries the estimated posterior mean effect of income is close to zero for some latent populations. In France, income has opposite effects on different latent populations. The next step is to investigate how that latent heterogeneity

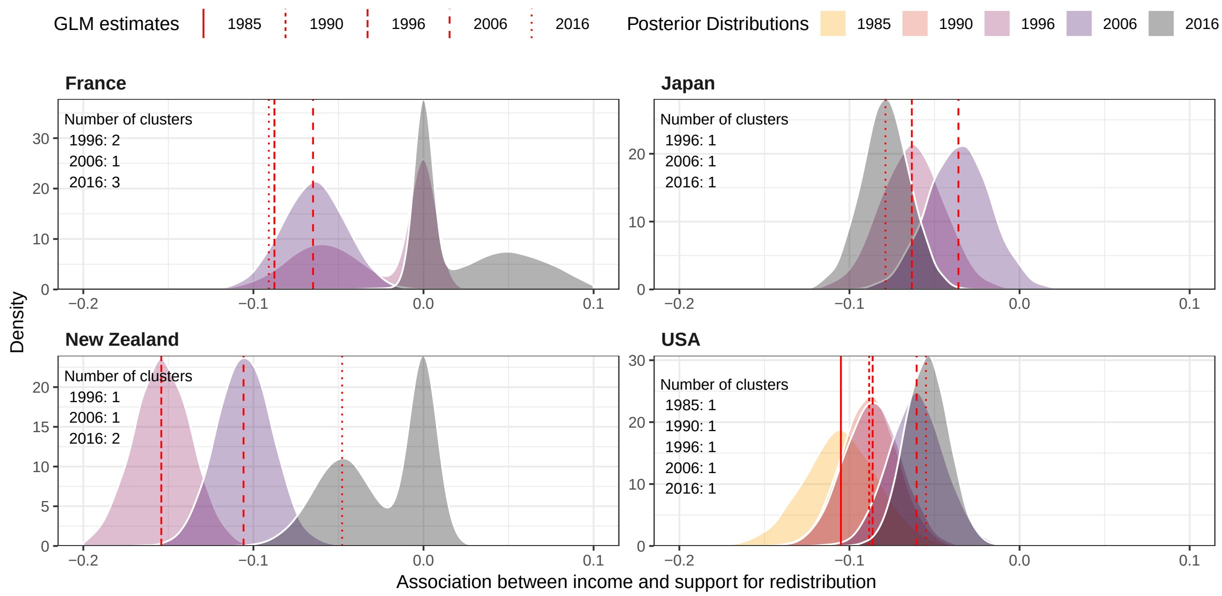


Figure 2.7: Posterior Distribution of Linear Effect of Income on Support for Redistribution for France, Japan, New Zealand, and the USA.

affects our conclusions about polarization in the society and between income groups. The next section turns to that point.

2.5.2 Polarization of Redistributive Attitudes in OECD Countries

Having established that there is latent heterogeneity in the association between income and support for redistribution in a large number of cases in our working example, the next step is to investigate how that affects our analysis of alienation, antagonism, and polarization in the societies and between income groups.

Table 2.3 presents the overall polarization computed for all countries and years. Both the values computed assuming homogeneity ($\hat{P}^{nohet}(f)$) and relaxing that assumption ($\hat{P}^{het}(f)$) are presented. The Table shows, first, that when there is just one cluster, assuming homogeneity of political attitudes within observed groups or relaxing that assumption does not change the estimated values of polarization, as expected. However, when there is latent heterogeneity in the political attitudes, assuming the contrary leads to underestimates of polarization. Second, polarization does not increase monotonically with the number of clusters. The polarization depends on the distribution of attitudes and the linear associ-

Table 2.2: Comparing Polarization in OECD Countries with and without homogeneity assumptions

	1985			1990			1996			2006			2016		
Country	Clusters	$\hat{P}^{nohet}(f)$	$\hat{P}^{het}(f)$	Clusters	$\hat{P}^{nohet}(f)$	$\hat{P}^{het}(f)$	Clusters	$\hat{P}^{nohet}(f)$	$\hat{P}^{het}(f)$	Clusters	$\hat{P}^{nohet}(f)$	$\hat{P}^{het}(f)$	Clusters	$\hat{P}^{nohet}(f)$	$\hat{P}^{het}(f)$
Latvia	–	–	–	–	–	–	2	0.22	0.8829	1	0.1972	0.1975	3	0.2077	1.574
Japan	–	–	–	–	–	–	1	0.3254	0.3245	1	0.2009	0.2002	1	0.278	0.2771
Canada	–	–	–	–	–	–	1	0.2484	0.2473	1	0.229	0.2274	–	–	–
Switzerland	–	–	–	–	–	–	4	0.2491	1.5588	1	0.2365	0.2353	1	0.1983	0.3454
USA	1	0.3858	0.3843	1	0.3111	0.3099	1	0.334	0.3333	1	0.2398	0.239	1	0.3097	0.3092
Australia	1	0.222	0.2221	4	0.2562	1.6227	–	–	–	1	0.2493	0.2488	1	0.3143	0.3129
Ireland	–	–	–	2	0.2435	0.9047	2	0.3403	0.5953	1	0.2503	0.2496	–	–	–
France	–	–	–	–	–	–	2	0.343	1.0471	1	0.2773	0.2767	3	0.2954	1.0042
UK	1	0.3378	0.3367	2	0.3268	0.6538	1	0.3638	0.363	1	0.2776	0.2769	1	0.2204	0.2197
New Zealand	–	–	–	–	–	–	1	0.3646	0.3634	1	0.3024	0.3012	2	0.2096	1.1429
Czechia	–	–	–	–	–	–	1	0.3982	0.3985	1	0.309	0.3088	–	–	–
Sweden	–	–	–	–	–	–	1	0.3971	0.3965	1	0.3425	0.3418	1	0.2559	0.2553
Hungary	–	–	–	2	0.3029	0.5872	3	0.3205	0.887	2	0.2447	0.5393	3	0.1408	0.9821
Germany	–	–	–	4	0.2662	1.4559	4	0.2861	1.5292	2	0.2736	0.5413	3	0.197	1.4256
Slovenia	–	–	–	–	–	–	2	0.3874	0.6117	2	0.2593	0.5926	3	0.3089	1.0421
Israel	–	–	–	1	0.2973	0.2947	–	–	–	2	0.2354	0.9096	3	0.1462	1.1999
Poland	–	–	–	–	–	–	3	0.2714	0.9708	3	0.2726	0.9759	–	–	–
Norway	–	–	–	1	0.3019	0.3017	1	0.2992	0.2991	2	0.3127	0.9931	3	0.2955	1.3132
Philippines	–	–	–	–	–	–	–	–	–	2	0.0861	1.0802	2	0.1575	1.2652
Spain	–	–	–	–	–	–	–	–	–	3	0.1581	1.3509	3	0.1789	1.2289
Russia	–	–	–	–	–	–	2	0.2713	0.8495	3	0.1621	1.3696	3	0.2688	1.232

ation of socioeconomic features and preferences, as discussed in Section 2.2.3. Consider France and New Zealand in 2016. The former is less polarized, in spite of having more heterogeneity. Third, in the USA, there is a decreasing trend in the polarization of redistributive attitudes, as found by other studies (Fiorina, Abrams and Pope, 2005; Fiorina and Abrams, 2006; Fiorina, Abrams and Pope, 2008; Baldassarri and Gelman, 2008; Fiorina and Abrams, 2010; Lelkes, 2016).

What about the alienation and polarization between income groups? How does the latent heterogeneity affect that? The cases of the USA and France in 2016 are two excellent examples to illustrate that point. To isolate the estimated antagonism and polarization between income groups, we generated fitted values by varying income and keeping fixed gender (male), education (low), and age (average value). The posterior average of each cluster is used to compute the fitted values of the estimated income effect under no assumption of homogeneity (hdpGLM).

Figure 2.2 shows the results for the USA and France. The top row of the panel compares the estimates of the two models for the USA. Both models produced very similar estimates because a single cluster was found for that case. The bottom row of Figure 2.8 shows the estimates for France. Different from the USA, there are three latent subpopulations in France. For two of them (clusters 1 and 3), the effect of income has opposite signs. This result illustrates exactly the situation discussed in the previous sections and depicted in Figure 2.3. The preference of low-income people in cluster 1 is closer to the preference of affluent people in cluster 3 than to poor people in that cluster. This means that a cross-class coalition in the dimension of support for redistribution is much more likely in that scenario than in the USA. That is, the opinions are not as separated by the effect of income as they are in the USA.

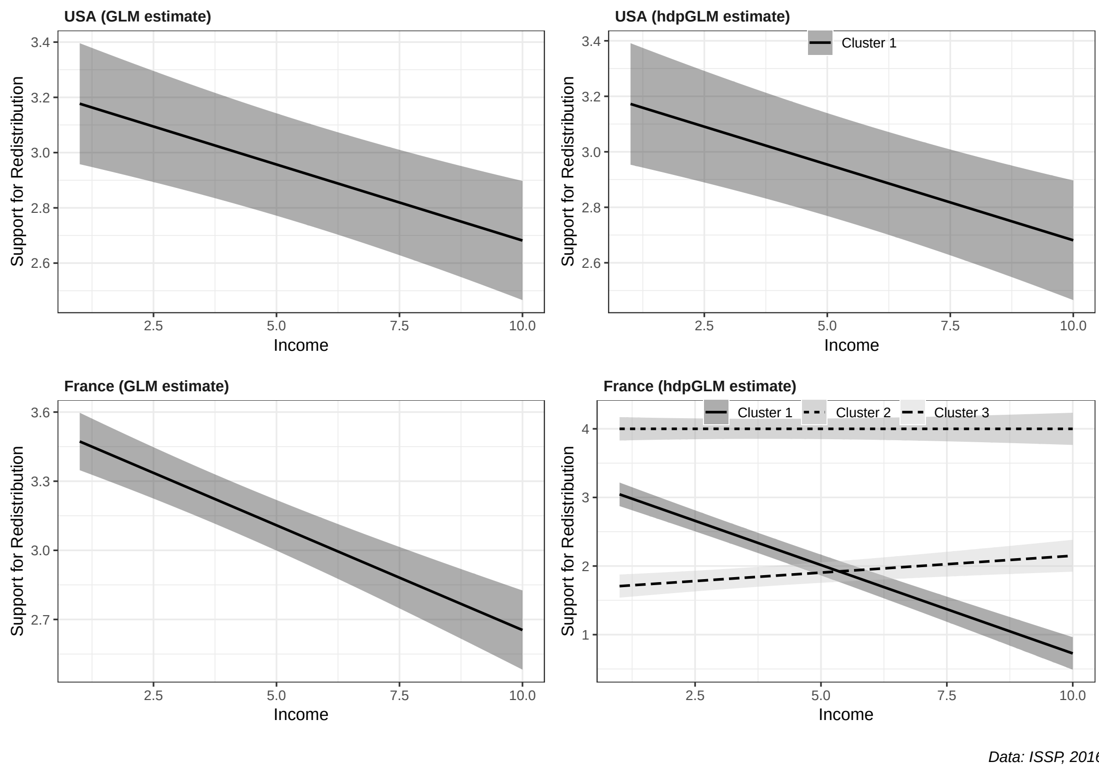


Figure 2.8: Comparing the fitted values of the effect income on support for redistribution for the USA and France using GLM estimates and posterior average of each clusters estimated with the hdpGLM

If the reader is not convinced how latent heterogeneity affects policy alienation between social groups, one numerical example should suffice. The estimated magnitude of the association between income and support for redistribution under the assumption of no heterogeneity (GLM estimate) is `-0.01`. Based on that result, the estimated average policy antagonism between any individual i and j who are both low educated males around 40 years old in the first income decile is zero ($\hat{\delta}(X_i = 1, X_j = 1) = 0$). The alienation between an individual in the first and in the last deciles, other things equal, is $\hat{\delta}(X_i = 1, X_j = 10) = 0.82$. Now, if we relax the assumption of homogeneity, the posterior expectation of the income effect produced by the hdpGLM is `-0.25` for cluster 1, and `0.05` for cluster 3. Based on that result, the estimated average policy antagonism between any individual i and j who are both low educated males around 40 years old in the first decile, and that belong to the same cluster, is zero ($\hat{\delta}(X_i = 1, X_j = 1) = 0$). For individuals with the exact same characteristics, but for whom the effect of income is different, that is, that belong to different clusters, the average estimated alienation is ($\hat{\delta}(X_{i1} = 1, X_{j3} = 1) = 0.93$). If we compare individuals in the first and last decile in different clusters who are otherwise similar in their observed characteristics, their estimated average alienation is $\hat{\delta}(X_{i1} = 1, X_{j3} = 10) = 0.48$. Hence, if we consider the latent heterogeneity in the effect of income, individuals that are similar in all aspects of their observed features (income, age, education, etc) in France can experience *larger* antagonism in their policy preferences than individuals in different extremes of the income scale. That does not happen if there is no latent heterogeneity, such as in the USA.

If that affects alienation, what about polarization between income groups? Continuing the example with France, consider the Figure 2.9. It shows the distribution of fitted values computed using values of the covariates from the original data and the estimates produced by the different models. The density of the raw outcome variable y is also displayed in the Figure. The top row displays the distributions of the low-income population (first to third income deciles), the middle row cases with middle income (fourth to sixth income deciles), and at the bottom, it displays high-income cases (seventh to tenth income deciles). First, we see that the distribution of fitted values produced by the model that relaxes the assumption of homogeneity (hdpGLM) fits much better the distribution of the data. Assuming homogeneity (GLM) the fitted values are compressed. The left corner of the panels displays the polarization *within* income groups. The values produced by the model that take into account latent heterogeneity is very close to the polarization computed using the raw data. However, if homogeneity is assumed, polarization *within* income groups are underestimated by large amounts (more than 10 times smaller).

Moreover, GLM overestimate the support for redistribution, although the overestimation is not the rule and it depends on the effect of other covariates. Here, if we had assumed homogeneity and ignored the possibility of latent heterogeneity, we had concluded that there is little or no polarization within income groups, and that even the high-income groups support redistribution (the average fitted value ($\hat{y}$) for the high-income group is 2.79, more than the neutral position, which is 2.5). Let's emphasize this point: In this example, the negative association is overestimated if the latent heterogeneity is ignored. So, if a researcher is making a statement about polarization by looking only at the magnitude of that association and ignoring the latent heterogeneity and the resulting shape of the distribution of the outcome variable, he would have concluded that the polarization is large between income groups. The polarization across groups would be overstated and understated within groups. If, on the other hand, he had looked at the association and the resulting estimated density of the outcome variable, but ignored the latent heterogeneity, then he would have underestimated the polarization instead. If the association between income and preferences is considered, the latent heterogeneity in that association is taken into account, and the resulting estimated density of the outcome variable is used to compute the polarization, then the estimated value of polarization would be very close to the one displayed by looking directly at the distribution of the outcome variable.

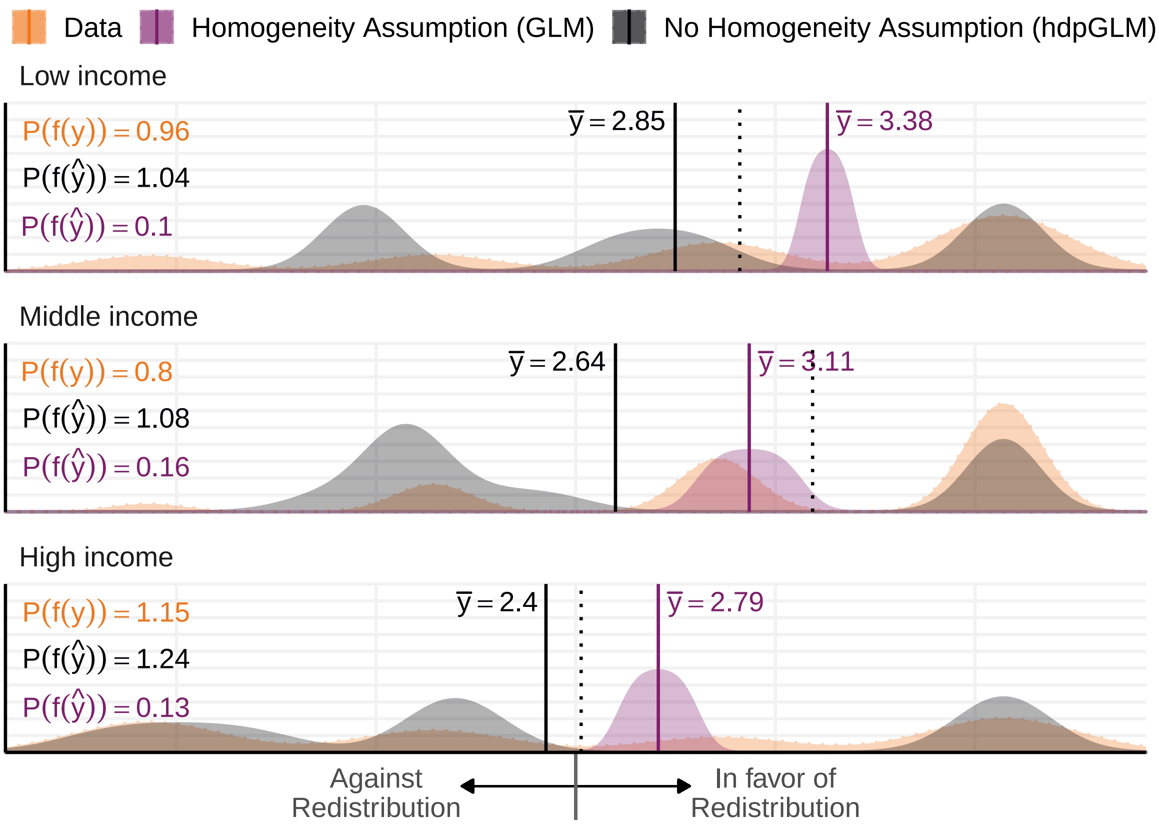


Figure 2.9: Actual and estimated distribution of preferences for redistribution and polarization of public opinion about redistribution in France in 2016 by income groups and modeling assumptions.

But if the polarization computed using either the raw outcome variable or the model that accounts for latent heterogeneity are similar, why to bother with the model? The answer is that it allows us to study the role of the socioeconomic features and the latent polarization between and within observed socioeconomic groups, which is important in political science research. The figure 2.10 illustrates that point. We continue with the case of France in 2016. To isolate the polarization between and within income groups, we fixed the value of all covariates but income, as before, and use the fitted values to compute polarization measures. We assume that all groups have the same size. That allows us to vary only the clusters and the income groups keeping everything else constant. On the left panels, we show the estimate of polarization under the assumption of homogeneity (top-left) and without that assumption (bottom-left). The right panel shows cross-class coalitions between *latent* social groups as well as latent within-class polarization. On the top-most right panel, we compute the polarization between low-income groups in the latent cluster 3 and high-income groups in cluster 1. The polarization between these groups is 0.43. It is *smaller* than the polarization *within* low or high income groups pooled from all clusters (two bottom-most right panels). In other words, affluent groups are more polarized in their attitudes toward redistribution than affluent and poor groups from different clusters. There is more cohesion in anti-redistributive attitudes in that cross-class latent group than among the rich.

The middle-top right panel shows the same result for a pro-redistributive cross-class latent group. The polarization in that cross-income group is also *smaller* than one that would emerge within either low or high-income groups alone.

Finally, the polarization that can emerge between poor and rich when we pool clusters together (left-bottom panel) is *smaller* than among the poor alone (bottom-most right panel). In sum, Figure 2.10 illustrates the relevance of taking into account latent heterogeneity in the association between income and redistributive attitude to characterize the polarization of redistributive preferences. In this illustrative example, the Figure reveals a *latent structure of polarization* about redistributive preferences. That structure cannot be revealed by looking at the raw outcome variable alone. Additionally, assuming away latent heterogeneity implies that this latent pattern of polarization/coalition across and within observed socioeconomic groups would remain unnoticed.

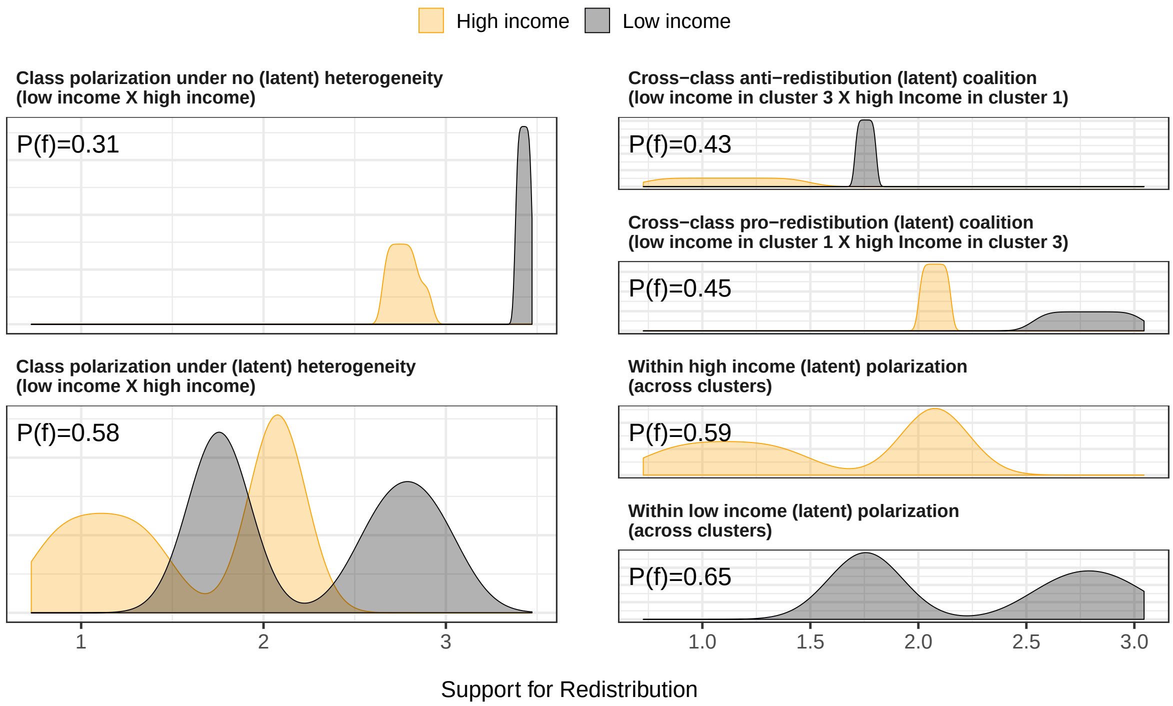


Figure 2.10: Latent structure of the distribution of preferences for redistribution and polarization in France in 2016 by income groups.

2.6 Conclusions

This paper developed a measure of polarization that is capable of combining the investigation of the determinants of political attitudes, latent heterogeneity on those determinants, and the polarization around those attitudes. It demonstrates that the heterogeneity in the effect of observed features has consequences for our understanding of political polarization between and within observed socioeconomic groups. When latent heterogeneity exists, polarization has a latent structure. We have exemplified our argument with data from OECD countries. In France in 2016, for instance, the (latent) polarization of redistributive preferences is larger within income groups than across them.

The example of *latent structure of polarization* found in the toy application in the paper can have important implication for theory development in political science. Many arguments about policy outcome, regime change, political revolution, party ideological differentiation, and protest behavior, to name a few, rely on the idea that the main redistributive conflict occurs along class lines. For those arguments to hold, the basic division of political attitudes between social groups - poor versus rich being a salient one - must apply. The empirical example in this paper shows that in some countries there might be a convergence of preferences connecting latent groups of different classes, as well as conflict of preferences within groups of individuals with the same observed socioeconomic features. The approach presented here can be used to investigate if that is the case, and to quantify those cross-groups coalitions or within-groups polarizations.

CHAPTER 3

Socioeconomic Positions, Perceptions, and Support for Redistribution

Abstract

The negative association between income and support for welfare policies has been widely documented in the literature. Although there are many explanations for why people would support redistribution, the predominant explanation for why income matters is that people evaluate welfare policies from the point of view of their material self-interest. Looking at their own pocket, low income groups see welfare policies as benefits for themselves, while high income see that as tax burdens over their own income. This paper presents an alternative explanation. Based on the political sociology, social psychology, and situated-cognition literature, it argues that the socioeconomic conditions of the individuals affect redistributive preferences because it affects their perception about the socioeconomic environment. Economic hardship among low income groups prompts them to be more aware of the constraints imposed by the socioeconomic conditions, which leads them to value equal opportunities, reject that meritocracy can justify inequality, and be much more pessimistic about the state of country's economy and unemployment. Those perceptions about the socioeconomic environment, affected by individuals personal socioeconomic conditions, affect their support for redistribution. Those perceptions, affected by individuals personal socioeconomic conditions, affect their support for redistribution. The empirical analysis is based on a series of structural equations estimated using cross-national data from the European Social Survey. The analysis shows that class-specific vales and perceptions about social reality account for up to 40% of the negative association between income and attitudes toward redistribution in the pooled data, and it reaches more than 100% in some countries.

3.1 Introduction

Is the negative association between income and support for welfare policies explained by the material interest of the different income groups? Assuming we take into account or hold fix the effect of other dimensions such as race (Lee and Roemer, 2006; Gilens, 2009), gender (Keely and Tan, 2008; Orloff, 2009), education (Alesina and La Ferrara, 2005), occupation (Svallfors, 1997), and risk of unemployment (Hacker, Rehm and Schlesinger, 2013; Rehm, 2009), etc., is there any reason, other than the income groups' recognition of their own material interest, that explains why income groups have different welfare policy preferences?

In this paper, we show that there is another reason. Based on the political sociology, social psychology, and social situated cognition literature, we theorize that the socioeconomic position (SEP) of the individuals not only inform them about their own material interest, but first and foremost aSEP affect values and perceptions. More precisely, we argue that socioeconomic positions shape policy preferences because SEP affects (1) perceptions about the causes of people's own economic situation, that is, the cognitive patterns of economic outcome attribution (luck, merit, situation, disposition, etc.), (2) perceptions about fairness and inequality, and (3) the way people perceive the social environment, including the current state of country's economy, unemployment, and the social and economic consequences for the different groups of state redistribution. Those SEP-dependent values and perceptions about how things *are* affect how people form their opinion about how things *should be*.

The political science literature has extensively documented the negative association between people's own economic conditions, usually measured by their income, and support for welfare policies. The magnitude of that association have been debated, but the negative average association itself is one of those few empirical facts that are almost uncontested in the literature. For the past 50 years, the default explanation for that regularity has been what we call here the *material self-interest (MSI)* hypothesis. The contemporary version of the MSI argument, since at least Romer (1975) and Meltzer and Richard (1981), is based on the rational choice behavioral model. In that version, income is negatively associated with support for redistribution (SfR) because of the material interest of the lower and upper classes. Low income groups benefit from redistribution, while upper class individuals pay more in taxes than they receive in social policy benefits[1]. The MSI hypothesis about

[1]That explanations based on class interest can be traced as far back as to the work of Karl Marx. According some scholars in that tradition, the "real" interest of the working class is not redistribution, but

the distribution of preferences has inspired an enourmous related literature, which includes topics that range from the relation between redistributive preferences and inequality (Lupu and Pontusson, 2011; Choi, 2019) to regime stability and change (Boix, 2003; Ansell and Samuels, 2010; Acemoglu et al., 2013).

Although alternative explanations argue that other factors condition or compete with the effect of income on attitudes toward redistribution, such as identity (Chen and Li, 2009), race (Lee and Roemer, 2006; Gilens, 2009), and altruism (Fong, 2001, 2007; Lupu and Pontusson, 2011), to mention a few, if there is any reason why a residual negative association between people's economic position and their attitudes about redistributive policies remains, that reason is understood to be the MSI. In the current literature, political scientists and political economists adopt almost by default that explanation (few exceptions are discussed ahead). To be clear: What has been broadly questioned or tested is that other factors matter *also and instead*, not *why* income and support welfare policies are negatively associated.

It is surprising that the explanaion for why we observe such a negative association remains almost unquestioned, despite of all the critique that the classic microeconomic approach based on the rational choice behavioral model underwent in the last decades[2]. Given the wide reliance of the literature on that explanation, it is even more surprising to find that the MSI hypothesis is not directly tested in empirical approaches that subscribe to it. One can search in vein for studies that demonstrate empirically that the reason why income and SfR are negatively associated is what the MSI proposition says. All we can find in the empirical sections of the literature is the evidence of the negative association, not *why* it is so.

This paper questions that conventional wisdom of the contemporary political economy of policy preferences. Based on the political sociology, social psychology, and social situated cognition literatures, we argue that the effect of income, or more broadly the socioeconomic positions of the individuals, on support for redistributive policies occurs largely because the former is associated with the emergence of a set of values and perceptions about the

overthrow the entire socioeconomic and political order, while the burgeoisie and the upper class groups fight to preserve the status quo in capitalist societies (Przeworski, 1980).

[2]The rational choice approach has been fruitful for studying some aspects of voting behavior (Cox, 1994) and political actors in structured institutional contexts, such as legislators in congress (Cox and McCubbins, 2005), or decisions of political leaders in international relations (Snidal, 2002). The approach has several limitations for studying public opinion and general social behavior, though. For a glimpse of critiques from different perspectives, see Harsanyi (1969), Sen (1977), Stoker (1992), Green and Shapiro (1996), and Bourdieu (2005).

world. Those values and perceptions, then, drive peoples' attitude about government responsibility, welfare policies, and redistribution.

Our argument provides a theoretical framework to connect two groups of scholarly work. On the one hand, recent political science research has shown how the subjective dimension, that is, values and perceptions, particularly about inequality (Gimpelson and Treisman, 2018), unemployment (Piketty, 1995; Cowell and Schokkaert, 2001; Rehm, 2009), and causes of economic success such as merit, luck, etc. (Alesina and Angeletos, 2005; Kraus et al., 2012) affect welfare policy attititudes. That literature focuses essentially on the effect of perceptions on policy preferences, but they treat only tangentially the effect of socioeconomic conditions on the emergence of those values and perceptions. When it comes to the role of income or individuals socioeconomic positions on preference formation, they still tend to adopt the MSI as the default explanation. On the other hand, the sociology, social psychology, and social situated cognition literature have long pointed out that the relative socioeconomic positions and status of the individuals can affect taste, evaluative behavior, practices (Bourdieu, 1974, 1984), cognition (Piff et al., 2010; Grossmann and Varnum, 2011), social values (Piff et al., 2010), and world views (Kraus et al., 2012). In other words, perceptions about the reality and social environment vary substantially by class. That literature, however, hans't progressed to investigate how those values affect preferences for welfare policies. We build a bridge between those two scholarly literatures, and present a theoretical approach that connects people's socioeconomic positions, values, perceptions, and welfare attitudes. In short, we argue that the objective socioeconomic positions of individuals shape their subjective perceptions and values, and those perceptions in turn affect their preferences for redistributive policies. That mechanism explains a great deal of people's redistributive policy attitude and why their socioeconomic positions affect their preferences.

In this paper, we demonstrate that groups in low socioeconomic positions, defined basically in terms of income, education, and occupation status, tend to perceive the economy and the government performance as doing much worse than do affluent groups. Lower class members are also more pessimistic when compared to objective measures of levels of unemployment in the country, as well as the chances of people in their occupation group to become unemployed. Moreover, the the poor tend to disbelieve in their capacity to influence politics, and to attribute both good and bad outcomes to circunstances rather than to agency. These dipositional versus situational attribution tendencies have been well documented in the literature (Kraus, Piff and Keltner, 2009; Kraus, 2010; Grossmann and

Varnum, 2011). For the poor, moral concepts, such as that of fairness, are entangled with ideas of economic equality. The upper class, on the other hand, tends to evaluate relatively well the economy when compared to the perception of lower classes, and they are more optimistic about both the country's unemployment situation and the living standard of unemployed people. They feel more confident in their capacity to influence politics and in control of their lives. They tend to attitube outcomes to hard work, agency, and merit. As a consequence, fairness does not necessarily depend on equality. For high income groups, inequality seems acceptable and can be justified to reward effort and hard work.

Using a series of structural equations and 2SLS estimators in an analysis of more than 20 European nations, we show that those class differences in values and perceptions are responsible for up to 40% of the effect of socioeconomic positions on desirability of welfare policies in the pooled data. When we look at each country separately, the percentage of the effect of economic positions on welfare policy preferences that occurs because the former affect perceptions range from 30% to more than 100%. Overall, the results indicate that individuals own socioeconomic positions affect preferences not simply because of the material interest of the different socioeconomic groups, but because SEP shapes perceptions about the socioeconomic environment and the fairness of its' operation, which in turn influence how individuals express their policy preferences.

The rest of the paper is organized as follows. The next section reviews the debate about the reason why income or, more broadly, the socioeconomic positions of the individuals affect their preferences about redistribution. That section also discusses the recent political science literature about the effect of perceptions on welfare policy preferences, and the sociology and social psychology literature about the relation between material conditions of different groups and their association with the development of cognitive patterns and perceptions about the socioeconomic environment. Then, we present our argument based on those considerations and draw predictions from our theoretical approach about people's attitudes toward government redistribution. The subsequent section describes the data and the empirical strategy to evaluate the theoretical predictions. The penultimate section contains the empirical analysis, first with pooled data, and then with some results for various European countries separately. The final section discusses the implications of our findings.

3.2 Theory

3.2.1 Why Income Matters for Redistributive Preferences?

Why does the socioeconomic position of individuals, other things equal, affect their attitudes toward government redistribution?

There are two main answers in the literature. The first and dominant perspective is rooted in the *homo-economicus* behavioral model. For the vast majority of the political economy literature, the reason why we need to consider socioeconomic positions, particularly income, on studies about redistritributive attitudes is narrowly and purely related to the effect of state taxation and redistribution on the individuals' and families' income. According to that perspective, we should expect a negative association between income and support for redistribution (SfR) because the latter reduces the consumption power of the upper class through taxes, and it does the opposite for the lower class through redistribution and targeted welfare policies (Romer, 1975; Meltzer and Richard, 1981). Many political economists would provide such an answer, without a second thought, to the question of why income affects redistributive preferences. We refer to that explanation as the *material self-interest (MSI)* hypothesis.

Even among scholars who demonstrate that other factors condition or compete with the effect of income on redistributive attitudes, the MSI hypothesis is widly accepted and often taken as given as the reason why SEP and SfR are negatively associated[3]. For instance, Rehm (2009) demonstrates that occupation-level unemployment risk is one of the two key factors determining redistributive preferences, the other one being income. The reason why the latter matters is because of "the rational-choice approach [which] derives an individual's attitude toward governmental redistribution from the effect of redistribution upon his or her net income." As another example, some authors have emphasized that social mobility affects preferences because policies are relatively stable over time, more so than social mobility for some people (Benabou and Ok, 2001; Piketty, 1995; Alesina and

[3]The list of works that exemplify that point is endless. See Meltzer and Richard (1981); Bolton and Roland (1997); Bean and Papadakis (1998); Roemer (1998); Bowles, Gintis et al. (2000); Fong (2001); Huber and Stephens (2001); Alesina and La Ferrara (2005); Alesina and Angeletos (2005); Gilens (2005); Alesina and La Ferrara (2005); Carsey and Layman (2006); Lubker (2006); Cusack, Iversen and Rehm (2006); Anderson and Pontusson (2007); Larsen (2008); Finseraas (2008); Rehm (2009); Chen and Li (2009); Jaeger (2009); Alesina and Giuliano (2010); Dallinger (2010); Baldwin and Huber (2010); Lupu and Pontusson (2011); Blofield and Luna (2011); Rehm, Hacker and Schlesinger (2012); Bechtel, Hainmueller and Margalit (2014); **?**); Bellani and Scervini (2015); Costa-Font and Cowell (2015); Kuziemko et al. (2015); Beramendi and Rehm (2016); Morgan and Kelly (2017); Walter (2017); Ballard-Rosa, Martin and Scheve (2017); Rueda (2018); Compton and Lipsmeyer (2019) and references therein.

La Ferrara, 2005). But "current income should be a good predictor of individual attitudes towards redistribution: the poor should be the main supporters of redistributive policies as in Romer (1975) and Meltzer and Richards (1981)" because, again, people care about how redistribution affect their net income (Alesina and La Ferrara, 2005).

Lupu and Pontusson (2011) proposes one of the few alternative explanations in the literature for why income and support for redistribution are associated, but it applies only to the middle class. The preference of the middle class depends on its relative income proximity to the poor. "Middle-income voters empathize with the poor [...] to the extent that they live in the same neighborhoods, send their children to the same schools, and circulate within the same social networks" (in Lupu and Pontusson (2011); see also McPherson, Smith-Lovin and Cook (2001)). *Paroquial altruism* and class affinity emerges among middle class members toward the poor if the life style of the former is closer to the later than to the rich, which results from relative proximity in income levels between the groups. I refer to this argument about the middle class preferences as the *class affinity hypothesis (CAH).* Even in that argument, the poor and the rich have opposite redistributive preferences for the same reasons put forward by the MSI argument.

There are two points that have been neglected in those works. First, although the MSI hypothesis is widely accepted, scholars have provided only indirect evidence of its validity. It relies on the empirically observed negative association between income - or other measure of socioeconomic status that combines income, occupation, and education - and welfare attitudes. That does not constitute evidence that the reason *why* we see that negative association is what the MSI argument states. The observed negative association between income and SfR does not constitute evidence for the CAH either. Is the poorer middle class folks more in favor of redistribution than their upper-middle class counterparts because they sympathize with the poor or because they are just poorer?

A second problem is theoretical. Those approaches assume that poor and rich perceive, in a similar fashion, the same underlying objective reality, as well as their relative position in that scheme. That is, both poor and rich attribute the same narrow meaning to government redistributive efforts and its consequences: it either takes or gives consumption power to different groups of people. Individuals need only to figure out if they are among the takers or givers. But, if socioeconomic positions of the individuals shape their social values and their perceptions about the social environment, the state of the economy, unemployment, and the consequences of redistribution, and if those perceptions and values matter for preferences, then the MSI cannot be the only reason why income affect SfR. The next two sections discuss these two points: why socioeconomic positions affect perceptions, and how the values and perceptions are connected to welfare preferences. We start with the latter.

3.2.2 The Effect of Values and Perceptions on Support for Redistribution

Along with the effect of socioeconomic positions, which according to the MSI hypothesis is expected to have an effect on preferences for redistributive policies, traditionally other *objective* socioeconomic characteristics of individuals have been used to explain preferences, such as race (Lee and Roemer, 2006; Gilens, 2009), gender (Keely and Tan, 2008; Orloff, 2009), education (Alesina and La Ferrara, 2005), occupation (Svallfors, 1997), employment Cusack, Iversen and Rehm (2006), union membership (Iversen and Soskice, 2009; Rueda, 2018), and risk of unemployment (Hacker, Rehm and Schlesinger, 2013; Rehm, 2009). In recent years, a growing trend in the political economy literature has focused on the effect of *subjective* assessment and *perceptions* rather than *objective* features on welfare attitues. That trend is supported by a diverse set of findings showing, that perceptions about the reality and the reality itself often don't match (Bavetta, Li Donni and Marino, 2017; Hauser and Norton, 2017; Duffy, 2018)

One of such trends focus on the case of inequality. A large literature shows not only that people tend to misperceive the actual levels of inequality, regardless of how the objective measure for comparison is constructed (Bavetta, Li Donni and Marino, 2017; Engelhardt and Wagener, 2017; Gimpelson and Treisman, 2018), but also that perceived rather than actual levels of inequality affect redistributive attitudes (Choi, 2019; Gimpelson and Treisman, 2018; Eriksson and Simpson, 2012). As Choi (2019) points out, it is reasonable to expect that ”voters who think the level of inequality is serious and unacceptable, irrespective of the level of actual inequality, demand more redistribution.” Hence, in addition to the perceived levels of inequality, the literature points out that perceptions about fairness of inequality maters. Inequality can be viewed as fair and acceptable if it reflects and rewards differences in effort, hard work, or merit. That acceptance diminishes support for redistribution (Kluegel and Smith, 1986; Miller, 1992; Piketty, 1995; Gilens, 2009; Alesina and Giuliano, 2010).

In the same vein, perceptions about unemployment and income risk can affect preferences. While part of the literature focus on objective risk of unemployment and prospects for upward mobility (Piketty, 1995; Benabou and Ok, 2001; Cusack, Iversen and Rehm, 2006; Rehm, 2009; Rehm, Hacker and Schlesinger, 2012), other authors argue that the perceptions of either becoming unemployed or improving living conditions in the future drives redistributive preferences (Ravallion and Lokshin, 2000; Cowell and Schokkaert, 2001; Manski, 2004; Rainer and Siedler, 2008). One of the critiques of the former approach that focuses on objective measures is precisely its assumption that people have a good grasp of the objective unemployment, risk, and mobility conditions (idem).

Moreover, a bulk of evidence shows that perceptions about the causes of economic outcome also affect redistribitive attitudes. Some authors use the term *cognitive contextualism* to refer to the tendency of attributing outcomes to context or exogeneous forces, while *cognitive voluntarism* captures the cognitive tendency of attributing outcomes predominantly to the own agent's choices and actions (Kraus et al., 2012). Alesina and Angeletos (2005) shows that Americans tend to believe more than Europeans that voluntary effort and hard work are rewarded with economic success. Those differences have implications for attitudes about welfare policies. People that believe that economic outputs are the result of merit and effort tend to show less support for redistribution. Conversely, those that attribute economic success to context rather than individual agency are more inclined to support redistributive policies (Piketty, 1995; Fong, 2001; Alesina and Angeletos, 2005; Alesina and Giuliano, 2010).

Cognitive tendencies to attribute outcomes to either the context or effort sometimes is connected to the idea of *deservedness*. According to the deservedness argument, people have different perceptions about how much themselves and others deserve and are entitled to receive in social benefits. The perception of deservedness can come from quite opposite underlying reasonings. In one view, people support redistribution if they perceive that others "deserve" it because they are in need or are not entirely responsible for their conditions. This is often refered to as empathy, or unconditional altruism (Hochman and Rodgers, 1969; Fowler and Kam, 2007). Conversely, perception of deservedness can be based on effort or merit (Miller, 1992; Romer, 1996; Roemer, 1998; Moffitt, Ribar and Wilhelm, 1998; Bowles, Gintis et al., 2000; Fong, 2001; Luttmer, 2001). Fong (2007) shows results of an experiment indicating that perception of deservedness based on effort have robust effects on support for social assistance (see also Fong (2001)). Romer (1996), argue that in the USA, social security was initially designed as a program to reward and provide insurance for those that contributed, not as a broad redistributive programs for those in need, regardless of their contribution. Authors refer to that type of determinant of policy attitude as *conditional altruism*, reciprocity, or equity principles (Walster, Walster and Berscheid, 1978; Bowles, Gintis et al., 2000; Fehr, Fischbacher and Gächter, 2002; Fong, 2007).

In yet another argument, researchers show that perceptions about the social costs of redistribution can affect preferences (Funk, 2000). In an experimental study, Durante, Putterman and Van der Weele (2014) shows that efficiency losses from redistribution can reduce the demand for redistributive transfers.

Finally, all that considered, we can expect that perceptions about overall economic conditions also affect support for redistribution. If people perceive that the country's economy is not going well, they may demand more government protection and intervention or, contrarily, less intervention if government policies are considered part of the problem.

This brief review by no means exausts the literature about the effect of perceptions on welfare attitudes, but it is enough to emphasize our point: The formation of preferences is not merely based on the individual's objective characteristics and their rational assessment of the objective features of the welfare policy options and its consequences to individuals own income, but it also depends on values and perceptions about inequality, unemployment, the country's economy, cognitive patterns of outcome attibution, perceptions of deservedness of the groups, and the social costs of the redistribution.

Notwithstanding its volume, there are two gaps in that literature, however, that this paper addresses. First, values and perceptions are typically treated just as a competing alternative explanation to the other main explanatory factors, one of which is material self-interest. The MSI, as the argument usually goes, provides the reason why we should account for the individuals' socioeconomic positions. Because those recent studies focus primarily on isolating the effect of perceptions on preferences, socioeconomic positions remain theoretically disconnected of the formation of social values and perceptions. That understanding is reflected in the empirical treatments, which use indicators of self-interst - captured indirectly, for instance, by individuals' income - alongside indicators of values and perceptions. That is, questions measuring perception (e.g., about inequality or unemployment) and measures of socioeconomic positions (e.g., income) enter the regression models as side-by-side additive covariates. So, those empirical tests only access if values and percetions matter for redistribution after controling for income levels or vice-versa. They pay less attention to *why* income matters (again, MSI is assumed to explain why), or how income and perceptions are related.

As a result, the second gap in that literature is that it pays little attention to why and how those perceptions emerge. Such a question is treated at best tangentially in that literature, ignoring or overlooking that there is a connection between the objective socioeconomic positions of the individuals and their perceptions[4]. Such a connection has important implications for our understanding of the mechanisms connecting socioeconomic positions and policy preferences. The next two sections discuss that point, starting with the relation between socioeconomic positions and perceptions.

3.2.3 The Effect of Socioeconomic Positions on Values and Perceptions

It is by now well documented that people's choices are not a result of pure rational consideration of objective pros and cons of the available options, but it is affected by subjective tendencies and perceptions (Nisbett and Ross, 1980; Tversky and Kahneman, 2000; Kahneman, 2011). The previous section discussed how subjective perceptions, e.g., about inequality and unemployment, affect welfare policy attitudes. Are those perceptions ramdonly distributed in the population? What do those preceptions depend on?

Sociologists have long argued that the socioeconomic resources of individuals matter for their taste, perceptions, values, and dispositions (Bourdieu, 1974, 1984, 2005). Different classes develop different tastes for cultural goods (Bourdieu, 1984; Snibbe and Markus, 2005) and material objects (Stephens, Fryberg and Markus, 2011). Atkinson (2013) shows that people's perception about their own control over their future market outcomes "seems to be stratified by position in the social space of classes and compounded by struggles within the economic and bureaucratic fields." (see also Atkinson (2010)). Socioeconomic positions matter because perceptions are affected by the life experiences, opportunities, the material constraints that the individuals of different classes face, and the struggles they encounter to provide for their families and themselves. That is, "particular conditions of existence - i.e. greater or lesser distance from material necessity - yielding objective probabilities of having certain experiences, of accessing certain goods and services and of undertaking certain movements within the social space [...]. Repeated experience of these probabilities as they manifest in the events and interactions of quotidian practice, through the build-up of typifications and associations [...], tend to engender subjective anticipations" (in (Atkinson, 2013), p. 646; see also Bourdieu (1974, 1984, 2000)).

[4] For instance, the central focus of Fong (2001) is the effect of perception of self-determination versus exogenous-determinantion, a.k.a. voluntarism vs contextualism, so she only speculates about why some people perceive that their outcome is due to their action (voluntarism) or to exogenous forces outside of their control (contextualism): "People who believe in exogenous-determination may be those who have low-mean, high-variance incomes [...], those who believe in self-determination may simply be people who have higher-mean, lower-variance incomes [...]" (see also Gimpelson and Treisman (2018), note 34).

In recent years, the effect of social class[5] on perceptions has gained much attention and emphasis in the social psychology literature. From very different perspectives, that literature has pointed out the influcence of social class on aspects that range from biological responses to the environment to subjective constructs such as values, tastes, and perceptions about reality. They have shown, for instance, that individuals from lower class are more likely to experience elevated heart rate, coronary disease, high blood pressure, and to perceive high hostility and threat in social interactions (Chen and Matthews, 2001). Experiences in the everyday life and the concerns about material hardship affect overall psychological states and perceptions about reality, which is potentialized by the negative health outcomes that result from those circunstances (Adler et al., 1994; Lachman and Weaver, 1998). Lower-class individuals are more likely to sense that they are not in control of their lives (Johnson and Krueger, 2005) or emotions (Kraus, Piff and Keltner, 2009), contrary to upper-class folks. They believe less in their own efficacy and capacity to achieve various goals, and feel more constrained by external forces than upper class members (Gurin and Gurin, 1970; Gurin, Gurin and Morrison, 1978; Lefcourt, 1981). Those findings are consistent with recent research that indicates that the lower class tend to attribute to the context both good and bad life outcomes, as well as the reasons for existing income inequality (Grossmann and Varnum, 2011). Upper class, on the other hand, has higher propensity to express that they have freedom of choice, and they tend to endorse essentialist theories of social inequalities to justify class economic differences, which includes attributing inequality and life outcomes to agency, effort, merit, and biologically inherited abilities[6] (Kraus, 2010). Class affects not only perceptions about social reality, the causes of inequality, agency, and how other classes are perceived, but also the degree of endorsement to equalitarian social values (Piff et al., 2010).

That literature goes further, and experimental studies suggest that class differences in perceptions and values help to explain "why upper-class individuals [oppose] more restora-

[5]Term often broadly refer to the individuals' material conditions and their access to a certain group of goods and services. That is, different classes have different consumption power and resources that determine their access to different goods. Although the most obvious indicator is income, it can include related features such as education, age, and occupation. While income and education are often used in political science and economics, occupation status and social class schemes based on occupation are often used in sociology. Social psychology, development economics, and health psychology often use the concept of socioeconomic status (SES) to capture essentially the same idea (Bollen, Glanville and Stecklov, 2001; Cirino et al., 2002; Kolenikov and Angeles, 2009; Berzofsky et al., 2014). We consider these differences in the section below that describes the data used for the empirical analysis.

[6]As an illustrative example, in an interesting study Mahalingam (2003) shows that upper class is more likely to adopt folk essentialist theoris of social classes, e.g., that a transplanted brain from a rich person can make the person rich.

tive policies, [such as] providing education opportunities, [or] ensuring tax relief for poorer people [...]" (Kraus, 2010). The next section builds upon this and the other arguments presented earlier.

3.2.4 Socioeconomic positions, Social Cognition, and Redistributive Attitudes

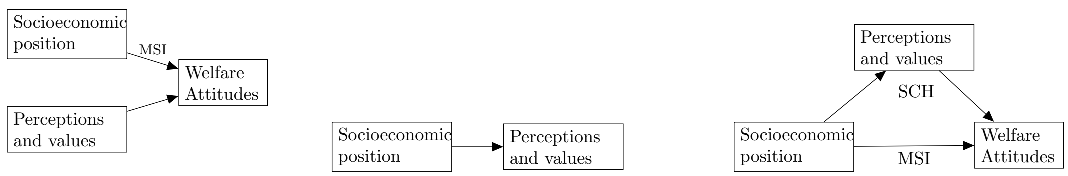
Based on the political sociology and social psychology literatures, we offer a complementary explanation to the classical MSI hypothesis for why socioeconomic positions are associated with welfare preferences. Our explanation connects, on the one hand, the political science literature about the effect of perceptions on policy preferences and, on the other hand, the sociology and social psychology literatures about the effect of individuals' material conditions on their perceptions.

Values and perceptions are not randomly distributed in the society. Because of the economic conditions and life circumstances people are exposed to, different classes develop different values and perceptions about social justice, fairness, self-determination, market and economic conditions, and social opportunities. Class-specific patterns of perception and values emerge because socioeconomic positions of the different classes dictate their typical life experiences, their material security, comfort or deprivarion, and their welfare anxieties and possibilities[7].

That argument is aligned with Kraus et al. (2012) (see also brief discussion in Alesina and Giuliano (2010), p. 115), who present a *social cognitive* approach that combines insights from sociology, health psychology, and situated cognition perspectives. That literature provides the theoretical justification for why perceptions differ: They are grounded on objective economic positions of the individuals, which determines their life experiences. As Kraus et al. (2012) argue, socioeconomic conditions "leads to predictable social cognitive thought patterns and worldviews that are not idiosyncratic, but rather shared, upheld, and promoted by people in similar circumstances", which leads to "coherent set of social cognitive tendencies and guide patterns of thought, feeling, and action" (Kraus et al., 2012, p. 547).

[7] As Atkinson (2013) puts it "[D]istance from necessity, provides differing degrees of security insofar as it endows opportunities [...] and safety nets [...], [leading to different] abilities to be able to take for granted what one has in the present and use it as a base for projecting oneself further into the future." In the same direction, Manstead (2018) argues material conditions of the different classes produce different "identity, cognition, feelings, and behaviour", which "make it less likely that working-class individuals can benefit from educational and occupational opportunities to improve their material circumstances."

We advance that literature by connecting those class-dependent values and perceptions to specific policy attitudes. More precisely, we argue that socioeconomic positions affect redistributive attitudes through and in good part because they affect perceptions about the social environment. Because this argument emphasizes cognitive perceptions as the mechanism connecting income and redistributive attitudes, we call it a *social cognition hypothesis (SCH)*. Figure 3.1 summarizes how our argument advances and differs from the previous literature.



(a) Material self-interest hypothesis (MSI) (discussed throughout the paper) and current approches about the effect of perceptions on welfare attitudes.

(b) Political sociology and social psychology arguments about the effect of socioeconomic positions on perceptions and values.

(c) Our social cognition hypothesis (SCH): Socioeconomic position affects welfare attitudes because it affects perceptions and values about the socioeconomic the environment.

Figure 3.1: Comparing different hypotheses in the literature and our argument about the association between socioeconomic positions of the individuals in the society, their values and perceptions, and their welfare policy preferences.

We can derive expecations about the policy preferences of the different socioeconomic groups from the SCH as follows. Individuals in low socioeconomic positions are more exposed to uncertainty and economic deprivation. They struggle much more than do upper class members to have access to goods, services, and job market and educational opportunities. They few more than other groups the burden of economic constraints in their daily lifes and the compression of their life opportunities. Hence, because of their everyday life experiences, we should expect that the individuals in lower socioeconomic positions tend to perceive the economy of their country as doing worse than do the members of affluent groups. When compared to the upper class, the lower class should also be more pessimistic about the levels of unemployment in the country, as well as the chances of people in their occupation group to become unemployed, despite of the objective measures of unemployment. The market reward is usually low. So, in accordance with other studies already mentioned, we should expect the that the lower class is more inclumed to display contextualist cognitive tendencies, attributing economic success to external conditions, as opposed to upper class members, who are more inclined to attribute success to merit and

Table 3.1: Summary of the empirically observable implications of our social cognition hypothesis (SCH) about the effect of socioeconomic position (SEP) on redistributive policy preferences (SfR) through its effect on perceptions.

		Perception that ...		
↑ SEP	⟹	↑ ... country's economy is doing well	⟹	↓ SR
↑ SEP	⟹	↑ ... unemployment is low (unemployment optimism)	⟹	↓ SR
↑ SEP	⟹	↑ ... unemployed standard of living is not very bad	⟹	↓ SR
↑ SEP	⟹	↑ ... inequality is fair/acceptable due to diff. in effort and merit	⟹	↓ SR
↑ SEP	⟹	↓ ... lower class deserve/get less than what they are entittled	⟹	↓ SR
↑ SEP	⟹	↑ ... benefits help to reduce inequality and poverty	⟹	↑ SR
↑ SEP	⟹	↑ ... benefits reduce productivity/make people lazy	⟹	↓ SR
↑ SEP	⟹	↑ ... benefits place strains to the economy and business	⟹	↓ SR
↑ SEP	⟹	↑ ... can influence political decisions	⟹	↑ SR
		Value as important ...		
↑ SEP	⟹	↑ ... wealth and economic success	⟹	↓ SR
↑ SEP	⟹	↓ ... safe surroundings	⟹	↓ SR

Note: The arrow ↑ (↓) indicates higher (lower) SEP (first column), higher (lower) degree of agreement with the sentence's statement (second column), or larger (smaller) support for redistributive policies (third column).

effort. In the same direction, we expect the poor to feel less than the rich that they are in control of their life outcomes. In accordance with such perceptions, for the poor, moral concepts such as that of fairness, is entangled with ideas of economic equality.

We expect that the upper class, on the other hand, evaluate relatively favorably the economy when compared to the perception of the members of the lower class, and is more optimistic about both the country's unemployment situation and the living standard of unemployed. They feel more confident in their capacity to influence politics and in control of their lives, and tend to attitube outcomes to hard work, agency, and merit. As a consequence, fairnes does not necessarily depend on equality. Inequality seems acceptable and can be justified to reward effort and hard work.

Those class-specific perceptions about the socioeconomic environment shape individuals attitudes about welfare policies. Therefore, the reason for support for redistribution is not only that policies add to or subtract from their pocket, but they *make sense* or are/aren't cognitively justifiable given how they perceive the social reality and their position in that scheme. The Table 3.1 summarizes the empirical expectations derived from our argument about the effect of socioeconomic position on perceptions, and the effect of the latter on suppot for redistribution.

To summarize the argument, on the one hand, our SCH advances the political science literature discussed earlier that focus on how perceptions affect policy preferences because we provides an explanation for why perceptions differ between social groups. On the other hand, we advance the sociology, social psychology, and social cognition literature by arguing that class-dependent perceptions and cognitive patterns imply different political attitudes toward government redistribution.

Before we close this section, it is important to observe two points. First, our approach cannot be called subjectivist because in our argument it is the objective reality that shapes what is perceived as such. That is, it is the very material conditions and concrete life experiences, opportunities, and struggles of particular groups in concrete socioeconomic contexts that shape what is perceived as the current state of affairs in the society.

Second, our argument is in great contrast with marxist theories of class counciouness. Marxist theorists argue that class, broadly defined in terms of a set of attributes centered on structural position of class members on the production system, creates the conditions for the emergence of class conciousness. That conciousness inform the classes, particularly the working class, of their own structural position and their material interests (Dahrendorf, 1959). The underlying reality of class dominance and exploitation is unique and uniquely perceive across classes . Similarly to the MSI hypothesis, this approach assumes a symmetric cognitive apprehension of the underlying reality across classes, which lead to different attitudes depending not on the perception, but on the objective positions of the individuals in the social structure. That is, all class become aware in the same way of the same objective material conditions, as well as their and the others position in that system. Lower classes, once conscious, want not only welfare and redistribution, but overthrow the system, while the upper class wants to preserve it. The redistribution and welfare policies, as alternatives to revolution, is a policy middleground adopted by social democratic parties in the 20th century, who considered that the democratic regimes open up the possibility to the working class to have access to political power via the democratic process and elections, which would enable them to adopt structural reforms in their favor (Przeworski, 1980). Our argument, on the other hand, points that material conditions of the classes don't lead to class conciousness, but instead it shapes values, tastes, perceptions, and behavioral dispositions that vary across classes (Bourdieu, 1974, 2000, 2005; Atkinson, 2013). Those values and perceptions affect people's attitude about the scope of government responsibility because it affects the meaning they attribute to government redistributive effort.

3.3 Data and Methods

To evaluate our argument empirically, we use cross-national data from the round 8 of the European Social Survey (ESS). Round 8 of the ESS was conducted in 2016 in more than 20 European nations. It is particularly useful for our analysis because it contains many questions asking the interviewees to state their perceptions about the country's inequality, economy, unemployment, fairness, and the effect of social benefits. It also measures various attitudes toward government redistribution and welfare policies at the individual-level, and it provides the socioeconomic characteristics of the individuals that we need to gain empirical access to our argument, including income and occupation. We selected the round 8 of the ESS because that survey contains a large variety of questions measuring perceptions and attitudes about redistribution.

Our first relevant variable is the socioeconomic position (SEP) of the individuals. This is the elementary independent variable for both the MSI and our argument. The political science, sociology, and social psychology literature have measured that concept in different ways. Income is the most commonly used indicator by the political economy literature to capture the effect of people's material self-interest on their attitude about redistribution (Alesina and Angeletos, 2005). In sociology, researchers often use class schemes based on market occupation, such as the Erikson-Goldthorpe-Portocarero (EGP) (Goldthorpe, 1980; Svallfors, 1997), European Socioeconomic Classification (ESeC) (Harrison and Rose, 2006), or the Socioeconomic Index of Occupational Status (ISEI) (Ganzeboom, De Graaf and Treiman, 1992; Ganzeboom and Treiman, 1996; Ganzeboom, 2010). Another common approach in sociology and social psychology is to use a socioeconomic status (SES) index, which is constructed using some combination of income, occupation status, families' household characteristics, etc. (for a discussion, see Adler et al. (1994); Bollen, Glanville and Stecklov (2001); Kolenikov and Angeles (2009)). SES is used to capture the position of individuals in the social structure and their "access to a set of economic, social, and cultural resources that determine their life chances and [. . .] living conditions" (Breen and Jonsson (2005), and see also Miech, Essex and Goldsmith (2001); Bradley and Corwyn (2002); Sirin (2005)). The main argument in favor of using such indexes rather than just income is that they provide a better picture of the material resources of families and individuals, their living conditions, and their life oppotunities because they incorporate into a single measure other resources such as class, education, and age.

In this paper, we construct four different indexes to capture the SEP. The first SEP index is composed just by income, which is available in deciles in the ESS data for each country and year in the sample. Using income as measure of SEP makes this study comparable with the others in the political economy literature that evaluate the impact of income on welfare preferences. The other three indicators of socioeconomic positions are composite indexes constructed using scores from a Principal Component Analysis (PCA). The first composite SEP index combines income and education. Our argument emphasizes how the socioeconomic positions affect welfare preferences through its effect of cognitive perceptions. Education is obviously an important component associated with both living conditions and cognitive assessment of the social environment. The second composite SEP index uses income, education, and the ISEI. ISEI captures the socioeconomic status associated with individuals occupation (Ganzeboom, De Graaf and Treiman, 1992; Ganzeboom and Treiman, 1996). This is important when we evaluate attitudes about unemployment and control for objetive occupation-level risk. Finally, we include age on the top of those three components to construct our third SEP composite index. Age is particularly important when we consider attitudes about responsibility of the government with the old. The details about the PCA and how the indexes are correlated are in the appendix, which also reproduces all the empirical analyses using each one of them separately.

Perceptions about the socioeconomic environment is the second important variable for our argument. We use a large set of variables capturing perceptions and values about inequality, fairness, the state of the country's economy, unemployment, causes of people's economic fate, unemployed standard of living, and about the effect of social policies. The complete list of variables and the summary statistics of those and the other indicators used in this paper are in the appendix C.1.1. We coded the variables that capture perceptions such that the higher the value, either the more the people agree with the statement or the more positive their evaluation is.

We use six different questions to measure attitudes about redistribution, which are our main dependent variables. The questions are described in the Table 3.2. The question "Government should take measures to reduce differences in income levels" is widely used by researchers to investigate redistributive preferences and it is included in all surveys used in this paper, so we pay particular attention to that question in the empirical analysis. For all variables, higher values indicate more support for redistribution.

We also include a series of control variables. *Occupation Unemployment Rate (OUR)* measure the objective uncertainty of future income loss (risk exposure). This is an objetive measure that represents the chances of becoming unemploymed. Rehm (2009) shows that risk exposure at the occupation-level computed using the ISCO88, aggregated at one digit

Table 3.2: Questions measuring normative redistributive attitudes in the ESS used here as dependent variables.

Welfare attitude
Government should take measures to reduce differences in income levels
Would you be against or in favor of having basic income scheme in your country
Government should provide social benefits only for people with the lowest income
Government should spend more on education and training programs for the unemployed and less in unemployment benefits
It's governments' responsibility to ensure reasonable standard of living for the unemployed
It's governments' responsibility to ensure reasonable standard of living for the old

categories, is associated with support for redistribution (see Rehm (2009) Table 2, p. 898) and it is highly correlated with income. Therefore, we include this variable in the analysis.

We include information about *religion attendance* (Scheve, Stasavage et al., 2006) , *gender* (Keely and Tan, 2008), *union membership* (Iversen and Soskice, 2009), and a variable indicating if the person is *unemployed* (Alesina and Giuliano, 2010). When the SEP indicator does not include education, occupation status (ISEI), and/or age, those variables are used as control.

3.3.1 Design

Our argument states that the personal material conditions of the individuals affect policy attitudes because it broadly affects the way they perceive their socioeconomic environment and the values they tend to adopt. To evaluate that mechanism, we estimate a series of structural equations using two stage least square (2SLS) estimators. Denote SfR the degree of support for redistribution, *Perc.* the variable that measures the perception about fairness, inequality, etc., SEP the socioeconomic position, and *controls* the k control variables. Let i indicate the individual in country j. The structural equations are:

$$\begin{aligned} \text{SfR}_{ij} &= \beta_0 + \beta_1 \text{SEP}_{ij} + \beta_2 \text{Perc}_{ij} + \beta_{3:k}^T \text{controls}_{ij} + \varepsilon_{ij} \\ \text{Perc}_{ij} &= \alpha_0 + \alpha_1 \text{SEP}_{ij} + \alpha_{3:k}^T \text{controls}_{ij} + \nu_{ij} \end{aligned} \tag{3.1}$$

We are interested in three main quantities. The first refers to the SCH and it is the effect of SEP on SfR that goes through its effect on perceptions. That quantity is given by $\beta_2\alpha_1$. The second represents the MSI hypothesis and it is captured by the quantity

β_1. Finally, we are interested in the share of the overall effect of the SEP on SfR that occurs because SEP affects the perceptions about the social environment. To obtain that quantity, we first estimate the following reduced equation (Baron and Kenny, 1986; Hayes, 2009):

$$\text{SfR}_{ij} = \lambda_0 + \lambda_1 \text{SEP}_{ij} + \lambda_{3:k}^T \text{controls}_{ij} + \varepsilon_{ij} \quad (3.2)$$

The quantity of interest representing the proportion of the total effect of SEP on SfR that goes through perceptions is $\left|\frac{\beta_2 \alpha_1}{\lambda_1}\right|$.

These quantities can be used to access the hypotheses stated in the Table 3.1. If, for instance, high SEP are associated with small SfR mostly because high values of the former make people perceive country's economy more optimistically, then we should expect high values of $\left|\frac{\beta_2 \alpha_1}{\lambda_1}\right|$, $|\beta_1| < |\lambda_1|$, and that the range of values of α_1, β_2, and $\beta_2 \alpha_1$ that are consistent with the data are away from zero (Baron and Kenny, 1986; Hayes, 2009).

3.4 Empirical Analyses

3.4.1 Descriptive

Table C.1 in appendix C.1.1 presents the descriptive statistics for all variables of the ESS 8. A detailed description and a complete analysis and results are in the Appendix. As a first approach to the data, and to evaluate the overall tendencies, consider Figure 3.2, which shows associations between SEP (income only), average support for redistribution (using the question "Government should take measures to reduce differences in income levels"), and perceptions about fairness of inequality, country's economy, and unemployment. The Figure uses pooled data. The left column shows the association between SEP (income) and perceptions. It shows that when income increases people tend to perceive that fairness does not depend on low income inequality[8]. Low income people are also much more pessimistic about the current state of unemployment than high income individuals, as shown in the bottom row of the left column. The middle row of the left column shows that as income increases, people have a more positive perception about the current state of their country's

[8]fn::The appendix show similar results for other policies, perceptions, and measures of socioeconomic positions.

economy.

The right column of Figure 3.2 shows how SEP and the perceptions displayed in the left column relates to support for redistributive policies. We divide the population in three income groups. "Poor" are those in the first three deciles of the income distribution in their country, "Middle Class" are those in the fourth to seventh deciles, and the rest are considered "Rich". The x-axis contains the answers to the question about perception, and the y-axis displays the average value of the answers to the question about support for redistribution by income group and perception answer. Consider the top panel of the right column, which shows the statistics using the question about perception of fairness of inequality. We see that the overall average of support for redistribution increases when people agree that low inequality is a requisite for a society to be considered fair. It is also true for each income group. The poor, rich, and middle class individuals who (strongly) agree that fairness requires low inequality all support more redistribution than their counterparts that disagree with that statement. Moreover, the difference in average support between income groups is different depending on their perception. Consider those that strongly disagree that inequality needs to be low for a society to be fair. The poor still supports redistribution on average (y-axis value larger than zero), but rich tend to oppose it (y-axis value smaller than zero). The difference in average support between income groups is not as big among those who strongly agree that fairness require low inequality (For simular findings, see Rueda, 2018). If we consider both the left and right columns of the first row we see evidence supporting our argument: As income increases, people are less inclined to accept that fairness requires low inequality, and the less they accept that, the less they support redistribution.

The same tendency appears in the bottom row of the right column of Figure 3.2, which indicates the perception about the percentage of unemployed. As income descreases, people hold a more pessimistic view about current percentage of unemployed in the country, and the more pessimistic they are, the more they support redistribution. The middle row of the figure shows the same pattern using perceptions about countries' current economic performance. These first-cut results are encouraging for our argument, but closer analysis is required. The next section presents the results with the structural equation estimates.

3.4.2 Analysis

We start by evaluating the results using pooled data and random effects for each country. Table 3.3 shows the results for two redistributive policies and two perceptions. We use

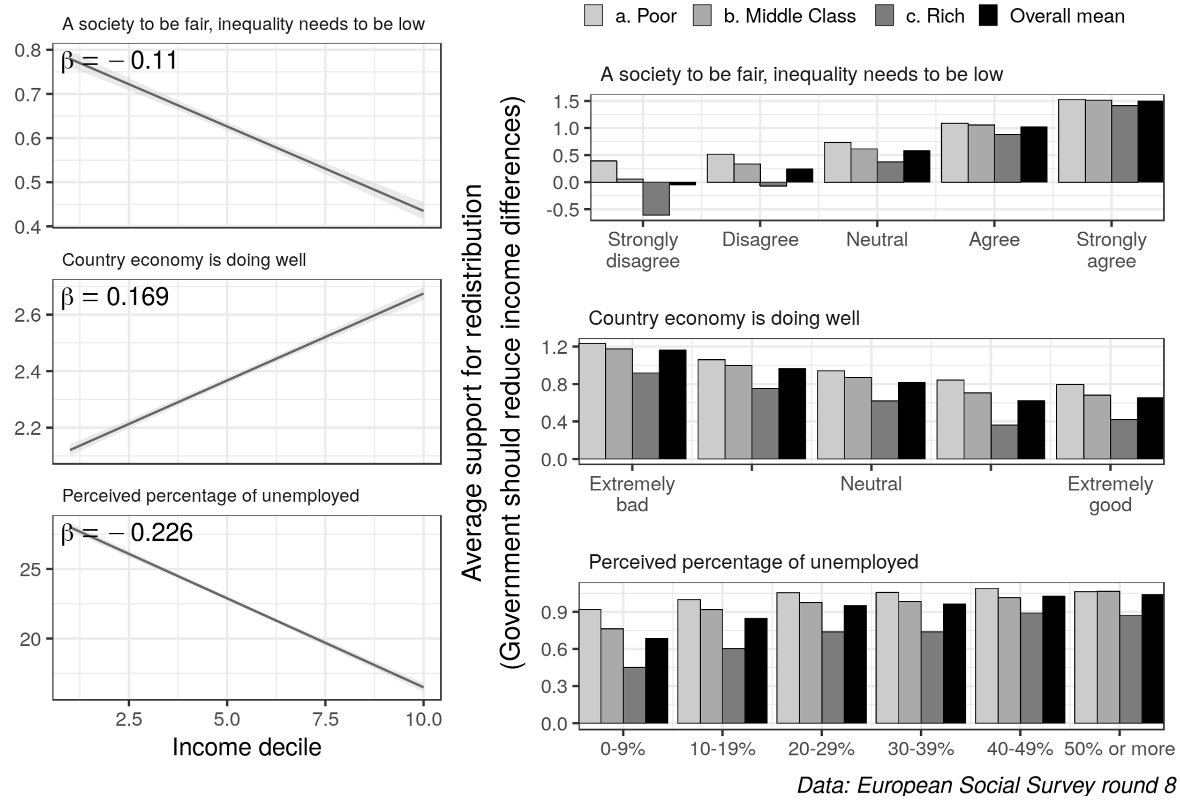


Figure 3.2: The effect of income on perceptions about fairness, inequality, country's economy, and unemployment (left column), and the average support for redistribution by income and perception groups

SEP index created using income, education, and ISEI[9]. All controls are included, but not shown. The second column of the Table shows the association between SEP and perception about unemployment[10]. The higher the SEP, the less people perceive unemployment with pessimism. The third and forth columns show the association between SEP and welfare attitudes about the responsibility of the government to provide assistance for unemployed people. We include perception about unemployment (unemployment pessimism) only in the estimation displayed in the forth column. We can see that SEP is negatively associated with welfare support in both cases, but when we include perceptions about unemployment the magnitude of the association diminishes. The results support our hypothesis about

[9]Analysis with other SEP indexes, policies, and perception measures are in the appendix.

[10]Unemployment pessimism in that table is a PCA score created using three questions on perceptions about unemployment: (1) Unemployed standard of living is not bad, (2) Perceived percentage of unemployed, (3) Perception about how likely to be unemployed soon. High values of the score means more pessimism. The same pattern appears if the questions are used separetely (see appendix).

Table 3.3: The effect of socioeconomic position (SEP) on values and perceptions (α) and on attitudes toward redistributive policies before and after perceptions are included (λ and β).

	Value/Perception: Unemployment			Value/Perception: Fairness and inequality		
	Unemployment pessimism (α)	*It's governments' responsibility to ensure reasonable standard of living for the unemployed* (λ *and* β)		*A society to be fair, inequality needs to be low* (α)	*Would you be against or in favor of having basic income scheme in your country* (λ *and* β)	
SEP[1] (income, educ, ISEC)	-0.1653 (-0.1757,-0.155)	-0.0578 (-0.0805,-0.0352)	-0.03 (-0.053,-0.0071)	-0.059 (-0.0693,-0.0488)	-0.0428 (-0.0566,-0.0289)	-0.0306 (-0.0443,-0.0168)
Unemployment pessimism			0.1647 (0.1408,0.1886)			
A society to be fair, inequality needs to be low						0.2061 (0.1902,0.2221)
Occup. Unemp. Risk	-0.0083 (-0.012,-0.0046)	0.0118 (0.0027,0.0208)	0.0134 (0.0043,0.0224)	-0.0019 (-0.0061,0.0023)	0 (-0.0057,0.0057)	0.0004 (-0.0052,0.0061)

Note: All regressions use random effects by country. Controls are not shown (Age, Male, Religion, Union, Unemployed)
[1] SEP: socioeconomic position.

perception of unemployment, and about the effect of perception as a mechanism connecting SEP and welfare preferences: We can see that as $\left|\hat{\lambda}_1\right| = |-0.058| > |-0.03| = \left|\hat{\beta}_1\right|$, and that the average effect of SEP that goes through perception of unemployment situation in the country is[11] $\hat{\beta}_2\hat{\alpha}_1 = -0.0272$. In total, around 47%[12] of the effect of SEP on SfR goes through its effect on perception about the unemployment situation in the country (unemployment pessimism).

The exact same pattern occurs if we look at the attitudes about having a basic income scheme in the country, and consider the perception about fairness of inequality, as shown in columns 4 to 6 of the Table 3.3. In that case, we can see that income has a negative effect on support for basic income schemes, but the magnitude diminishes if we control for perceptions $\left|\hat{\lambda}_1\right| = |-0.043| > |-0.031| = \left|\hat{\beta}_1\right|$, as should be the case when the perception about fairness and inequality matters for preferences and depends on income. The higher the SEP, the less one agrees that fairness depend on low inequality ($\hat{\alpha}_1 = -0.059$), and the less people perceive inequality as a requisite for fairness, the less they support basic income schemes ($\hat{\beta}_2 = 0.206$). Around 28% of the total effect of SEP on basic income support goes through the effect of the former on perception of fairness of inequality.

The Figure 3.3 shows similar results for yet another policy question. We use only income

[11] The 95% confidence interval is $(-0.0307, -0.02)$. Values computed using the 2SLS estimates and the approach presented in Imai, Keele and Tingley (2010); Imai, Keele and Yamamoto (2010); Tingley et al. (2014)

[12] It follows directly from $\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right| = \left|\frac{(-0.165)*(0.165)}{-0.058}\right| \approx 0.4694$

as indicator of the SEP for that figure[13], and the question considered is "Government should take measures to reduce differences in income levels." The Figure shows the role of perception about fairness and inequality. The results are presented using DAG, as those displayed in the Figure 3.1 with the summary of the hypotheses. The Figure can be used as a template for the other results and discussions because it concisely presents the main quantities of interest. The estimation procedure is the same as the one adopted to estimate the results displayed in Table 3.3. The top panel of the Figure 3.3 shows the total effect of SEP (income) on welfare preferences. The bottom panel shows the role of perceptions about fairness and inequality. Similarly to the results in the column five of Table 3.3, in which we used the SEP index composed by income, education, and ISEI, we can see in the Figure 3.3 that if we consider income only as a measure of the SEP, it is likewise associated with perceptions about the unfairness of inequality: The higher the income, the less people agree that fairness requires low inequality. Moreover, the more inequality is perceived as unfair, the more people support redistribution.

Those results are consistent with our initial exploration presented in the Figure 3.2 and with other findings in the literature that investigates the role of the perception of fairness of inequality on redistributive attitudes (Alesina and Angeletos, 2005; Fong, 2001). What has't been explored by previous research, however, is the role of SEP (or income) in shaping those values and perceptions. Fong (2001), for instance, regresses redistributive preferences on income (following the argument in the MSI hypothesis) and perceptions about the role of luck and opportunities as cause of poverty and inequality. His theoretical framework is guided by the hypothesis described by the item (a) of the Figure 3.1 (same as in Alesina and Angeletos (2005)). From the MSI perspective, Fong (2001) concludes that "income is a surprisingly poor predictor of redistributive" attitudes (see also Alesina and Angeletos (2005)). In light of our argument and the approach adopted here, we can reinterpret that conclusion. It is not the case that income does not matter when the perception of fairness is included. It seems to be the case only if we ignore how the SEP affects perception at the first place. The Figure 3.3 shows that typically around 28% of the total effect of SEP, as measure by income alone, goes through that mechanism. We will explore that point further below, when we discuss the fitted values of redistributive attitudes in some countries based on different theoretical perspectives, and then we return to this point about how ignoring the connection between SEP and perceptions to shape redistributive attitudes can lead to quite different conclusions about the importance of SEP in shaping

[13] Results are similar for other indicators. See appendix.

redistributive preferences.

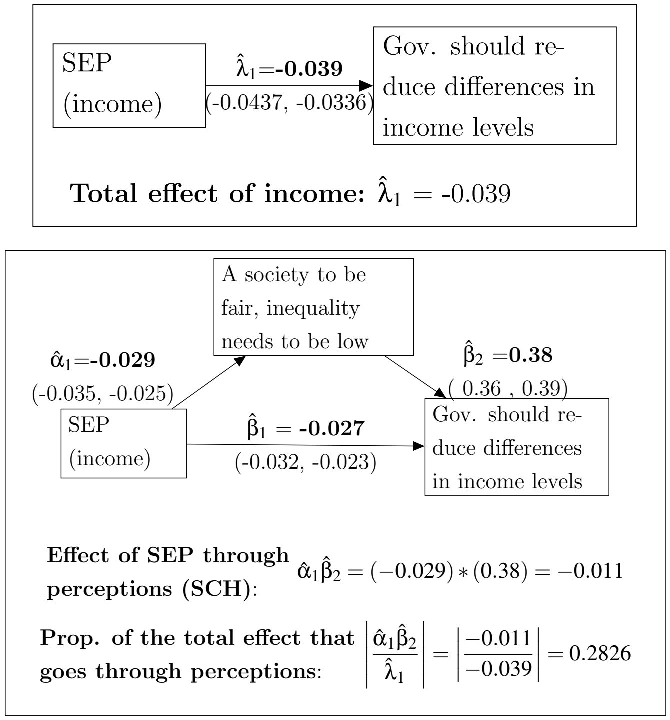


Figure 3.3: Estimates of the total effect of socioeconomic position (SEP) on preferences when perceptions are not included in the estimation (top panel) and the effect of SEP on preferences through its effect on perception (bottom panel)

Now, we expand our analysis to attitudes on six different policy areas, and evaluate the role of perceptions about varios aspects of individuals socioeconomic environment. The results are summarized in Figure 3.4. The y-axis of the Figure contains sentences that summarize different questions about people's perception on inequality, unemployment, country's economy, implications of social benefits to business and economy, and so on. The y-axis is ordered by how much the effect of SEP on preferences goes through perceptions. The left-most panel in the Figure shows the estimated effect of SEP on perceptions of different aspects of the social environment. Higher scores in those questions indicate the degree of agreement with the statement, or a good evaluation when that is the case. For instance, the first line shows that lower SEP is associated with the perception that unempolyed people do not really try to find a job. Hence, the poor tend to blame *others* unemployed by their situation. Note that this does not mean that they blame themselves for their own conditions. In the middle panel, we see that the more people perceive unemployment as lack of effort to find a job, the less they agree that the government should take care of unemployed standard of living (left-most upward triangle in the first row of the middle panel). The third panel shows that almost 90% of the effect of SEP on support for unemployment benefits is due to the SEP effect on perception about people's own responsibility to not find a job. The little horizontal bars crossing the point estimates represent the 95% confidence intervals, so it is easy to see the range of estimated values that are consistent with the data.

Another interesting result displayed in the Figure 3.4 is the effect of the perception that social benefits make people lazy. Interesting enough, the poor rather than the rich tend to believe that benefits have such a harmful effect on recipients' behaviour. But the more people perceive the benefits as promoting laziness, the less they support redistribution for low income groups and the more they demand spending in training programs for unemployed rather than unempolyment benefits. Around 80% of the effect of SEP goes though that mechanism when basic income schemes are at stake, and around 50% when it comes to unemployment benefits.

We repeat the above exercise for each OECD country individually. A summary of the results is shown in Table 3.4. For that Table, we used only the question "Government should take measures to reduce differences in income levels." We also display only the perception for each country that have the largest relative role in explaining the effect of SEP on redistributive preferences. The right-most column shows the share explained by the effect of SEP on perceptions. We can see two features in the table. First, the proportion of the total effect of income on SfR that goes through perceptions vary substantially by country. It goes from 17% in France to 780% in Spain. For most of the countries, that percentage stays around 30 to 40%. Second, the perception that matters the most vary as well. In most of the cases, perception about fairness of inequality explains the effect of SEP on support for redistribution more than any other case. That changes if we consider different policies, such as unemployment benefits (see appendix). For preferences about redistributing income from rich to poor, in Lithuania the effect of SEP that goes through perception of current country's economy is 1.16 higher than the overall effect of income alone. In Iceland, it represents 45% of the total. In Austria, the perception with most impact is about the effectiveness of the social policies to prevent widespread poverty. Due to theoretical focus and space limitations, it is beyond the scope of this paper to explore and explain those country-level variations, which we do elsewhere.

As briefly discussed above, the conclusions about how much SEP matters for redistributive attitudes depend on the theoretical perspective about the connection between SEP,

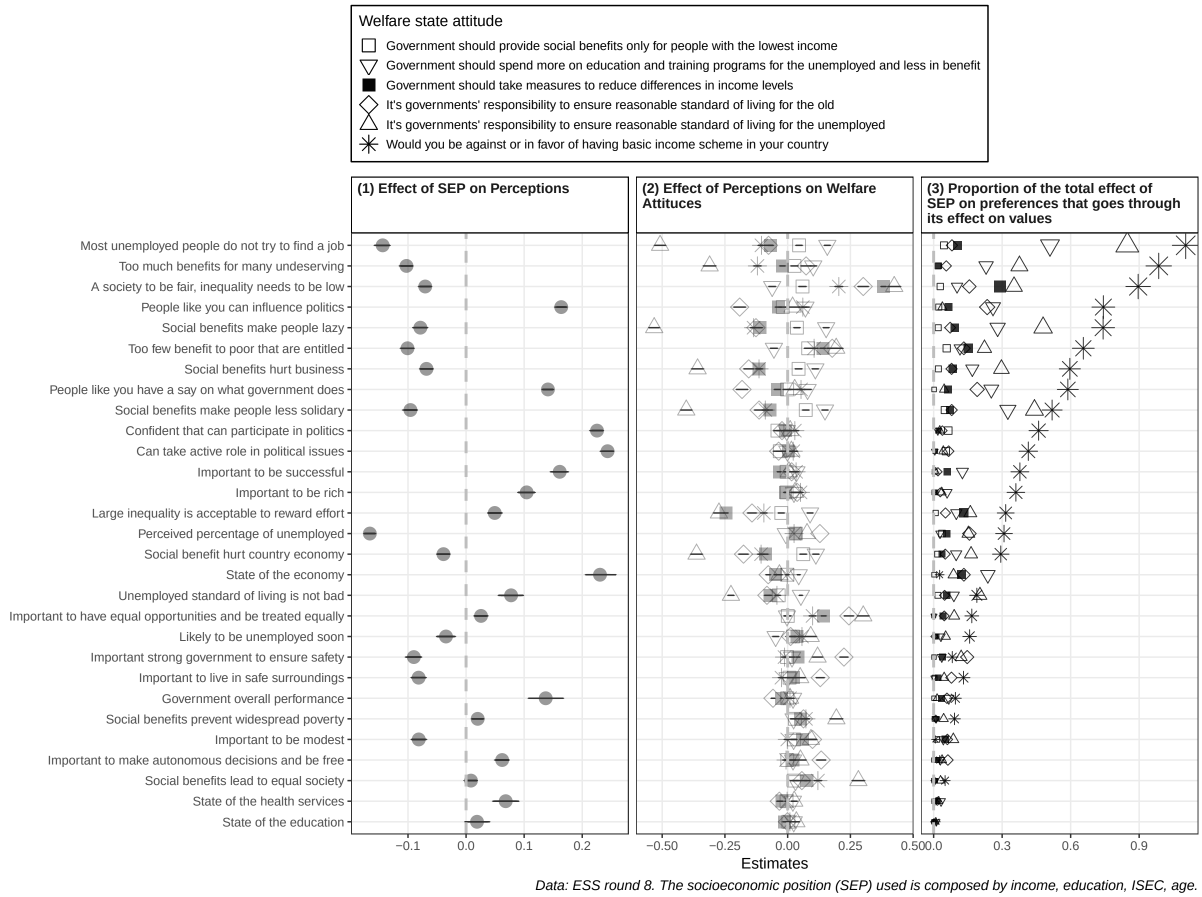


Figure 3.4: Association between SEP and perceptions, perceptions and welfare, and the proportion of the effect of SEP on welfare attitudes that goes through different values and perceptions.

perceptions about the socioeconomic environment, and welfare preferences. Figure 3.5 demonstrates that point. The Figure shows two countries selected from Table 3.4, Iceland and United Kingdom. The top row of Figure 3.5 shows the fitted values of the perception variable (y-axis) as function of SEP (x-axis). The bottom row shows the effect of SEP on support for redistribtion ("Government should take measures to reduce differences in income levels"). The bottom row displays three fitted lines. The solid line is the effect of SEP on SfR that goes exclusively through the effet of SEP on the perception, which is displayed in the y-axis of the plot imediately above it. This captures part of the SCH, in particular the mechanism stressed in this paper about the relation between SEP, perceptions, and welfare attitudes. The dotted line captures the MSI as currently adopted by the literature,

Table 3.4: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions.

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Prefer-ences	Proportion of the SEP effect mediated by Percep-tions
Spain	A society to be fair, inequality needs to be low	-0.0020	-0.0524	0.2972	7.7866
Portugal	Social benefits hurt business	0.0006	-0.0652	-0.0406	4.4119
Lithuania	State of the economy	-0.0143	0.2626	-0.0634	1.1643
Hungary	Large inequality is acceptable to reward effort	-0.0252	0.0943	-0.1956	0.7319
Estonia	A society to be fair, inequality needs to be low	-0.0761	-0.1277	0.3311	0.5556
Slovenia	A society to be fair, inequality needs to be low	-0.1232	-0.2004	0.3290	0.5352
United Kingdom	Large inequality is acceptable to reward effort	-0.0485	0.0777	-0.2958	0.4739
Austria	Social benefits prevent widespread poverty	0.0272	0.0670	0.1908	0.4700
Iceland	State of the economy	-0.1291	0.6655	-0.0889	0.4583
Czechia	A society to be fair, inequality needs to be low	-0.2097	-0.1928	0.4891	0.4497
Belgium	A society to be fair, inequality needs to be low	-0.1064	-0.1123	0.4242	0.4477
Netherlands	A society to be fair, inequality needs to be low	-0.1415	-0.0908	0.5436	0.3488
Germany	A society to be fair, inequality needs to be low	-0.0936	-0.0763	0.4243	0.3459
Italy	A society to be fair, inequality needs to be low	-0.0739	-0.0779	0.2997	0.3159
Poland	A society to be fair, inequality needs to be low	-0.2065	-0.1798	0.3525	0.3069
Switzerland	A society to be fair, inequality needs to be low	-0.1543	-0.1028	0.3890	0.2592
Ireland	A society to be fair, inequality needs to be low	-0.0961	-0.0693	0.3519	0.2538
Finland	Too few benefit to poor that are entitled	-0.1590	-0.1725	0.2063	0.2238
Sweden	Large inequality is acceptable to reward effort	-0.1202	0.0852	-0.3127	0.2216
France	A society to be fair, inequality needs to be low	-0.1745	-0.0851	0.3358	0.1638

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

in which perceptions and SEP can have independent effects and one can be held constant to evaluate the effect of the other. Under that approach, one would conclude that the effect of SEP is the one represented by the dotted line. However, if SEP affects the perceptions about inequality, unemployment, etc., and the latter affects welfare attitudes, as we have stated here, then the overall effect of income should be the one represented by the dashed line. In Iceland, under the usual MSI argument and the assumption of the independent effect of perceptions on welfare attitude, one would conclude that the marginal association between SEP and redistributive preferences is slightly positive. The picture changes completely is we consider how SEP affects perceptions about the country's economy in Iceland. The higher the income, the more the economy is perceived as doing well, which by its turn implies less support for redistribution.

A similar pattern manifests in the United Kingdom in the right column of Figure 3.5. For that country, the larger the SEP, the more people perceive inequality as acceptable to reward effort, and the more they accept that, the less they support redistribution. On average, 47% of the effect of SEP on support for redistribution goes through that mechanism, as shown in the last column of the Table 3.4. Figure 3.5 shows that the effect of SEP on support for redistribution is underestimated (dotted line) if we ignore its effect on acceptance of inequality. When we account for that effect, we see that the negative impact of income is larger, and part of the reason is because lower SEP reduces the acceptance of inequality, which by its turn increases support for redistribution.

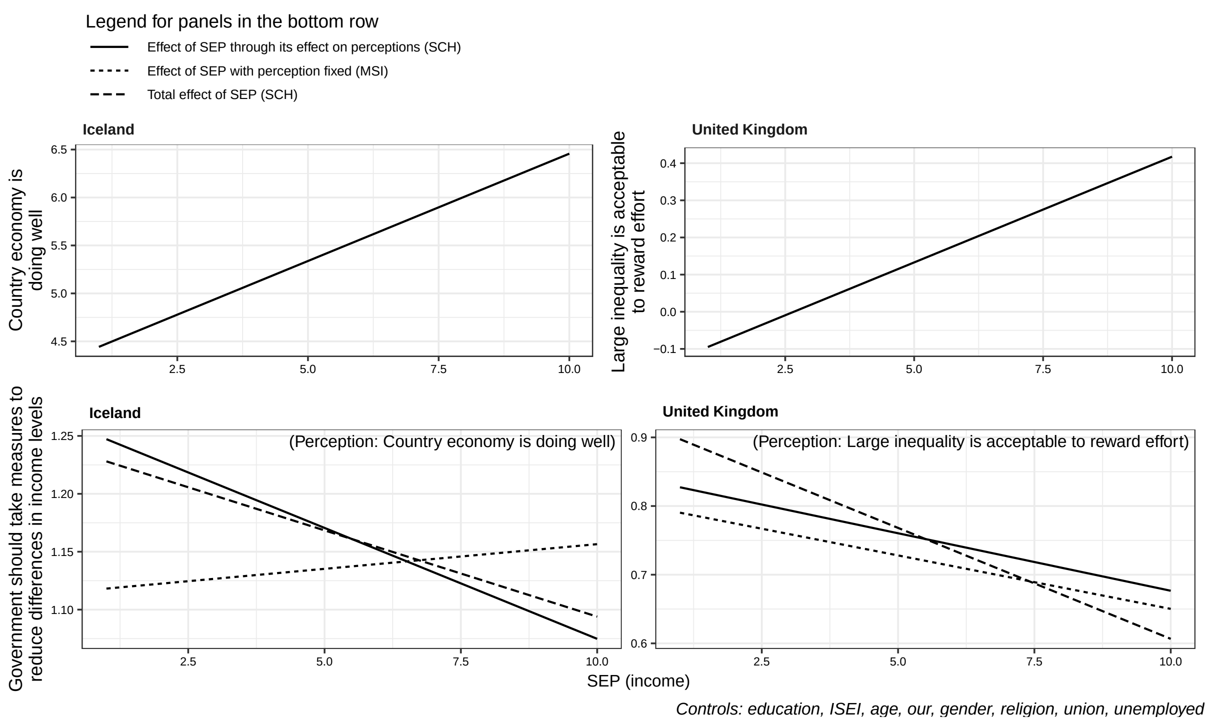


Figure 3.5: Comparing fitted values using the conditional association between socioeconomic position (SEP) and redistributive policy preferences for 2 countries from the Table 3.4 under the material self-interest hypothesis (MSI) and the social cognition (SCH) hypothesis

In sum, the set of empirical evidence presented here support our hypothesis. Perceptions affect redistributive preferences, as recent literature in the political economy of policy preferences demonstrates (Alesina and Angeletos, 2005). But this paper shows additionally that perceptions are not ramdonly distributed in the society. They follow a very predictable pattern that based on the socioeconomic positions of the individuals. So, the SEP affects redistributive attitudes in part because it shapes those perceptions.

The appendix contains various analyses to check the robustness of the findings presented here for the ESS round 8. We repeat the analysis using the ESS round 4 and the various rounds of ISSP, module Role of Government. The other surveys contain only a subset of the questions about welfare preferences shown in the Table 3.2. For the robustness check, we also used all four indicators of socioeconomic position (SEP), change the model specification by including/excluding control variables, and rerun all the analysis after multiple imputation of the missing values (King et al., 2001; Rubin, 2004). The details and the results are too numerous to be presented here, but the essential evidence that a substantively large share of the effect of SEP on welfare attitudes works through its effect on perceptions remains the same.

3.5 Conclusion

In this study, we present an alternative explanation for *why* individuals's personal socioeconomic positions affect their attitude toward state redistribution. The dominant approach in political science and economics assume that income or, more generally, socioeconomic positions are negatively associated with support for redistribution because of the material interest of the different groups: Rich prefer low tax and low redistribution because they have to pay for the policies and do not receive proportionally in benefits, while the poor demand more welfare policies and redistribution because they pay low taxes and the policies benefits them. One of the underlying assumptions of that argument, which is problematic from our perspective, is that everyone, regardless of their class, education, or economic status, *perceives* - or develops the same cognitive pattern to think about - the underlying issue at stake. For everyone, redistribution means purely material costs-and-benefits, and people just need to figure out if they are net receivers or payers in that scheme. As the most common arguments in the political economy of redistributive preference goes, that accounts for the reason *why* income matters for redistributive preferences.

We challange that mechanism as the unique explanation for *why* income affect redistributive preferences, which in our understanding presents a rather simplistic view about the role of people's economic conditions on shaping their political attitudes. We argued instead that the living conditions, opportunities, and stroggles associated with specific socioeconomic positions of the individuals shape how they perceive their social environment. Despite of the objective measures, people in different strata have different perceptions about the current performance of their country's economy, unemployment levels, their own risk of becoming unemployed, and the effect of social policies. We demonstrated that the lower the socioeconomic position, the more pessimistic people's perception are. Moreover, based on sociology, social psychology, and social cognition literatures, we argue that the living conditions of lower socioeconomic groups are connected to cognitive patterns that lead them to reject inequality and attribute their economic fate to the circunstances. Conversely, favorable opportunities and material comfort of affluent class make people in that group more likley to develop voluntaristic views of people's economic situation, attributing success and material conditions to people's effort and merit. Those class-dependent cognitive patterns and perceptions, then, affect people's normative attitude about welfare policies.

Arguments about the impact of perceptions about fairness, inequality, and merit on redistributive attitudes are not new. Recent political science literature has turned their attention to how those subjective factors affect redistributive preferences. What that literature misses is the connection between those perceptions and the material conditions of the individuals. The sociology, social psychology, and social cognition literature have argued for long that values, perceptions, and cognitive patterns are class-dependent. This literature, however, haven't fully explored how that feature impact people's policy preferences. The main contribution of this paper is providing a theoretical framework connecting those pieces, and demonstrating that socioeconomic positions affect welfare attitudes not only because it makes people to think about the costs and benefits of the policies for their own pocket, but because it shape the way people perceive their socioeconomic environment.

As a general take away, this paper demonstrates that we have to be very careful to work through causal chains to understand more fully what our "best controls" and design imply, and what our partial-coefficients or treatment effects actually mean. As we demonstrated, our understanding about *why* and *how much* income or, more generaly, socioeconomic positions matter for redistributive preferences is deeply affected by our theoretical and empirical perspective.

APPENDIX A

Hierarchical Dirichlet Process Generalized Linear Models

A.1 Markov Chain Monte Carlo Algorithms

The proof of the proposition .1 is the following.

Proof 1 (Blocked Gibbs sampler for hdpGLM)**.** *The full conditional of* τ *is given by*

$$p(\tau \mid \theta, \pi, Z, y, X, W, C) \propto p(\theta \mid W, \tau) p(\tau) \propto \prod_{d=1}^{D_x+1} p(\theta_d \mid W, \tau_d) p(\tau_d)$$

For each $d = 1, ..., D_x + 1$ *we have*

$$p(\tau_d \mid \cdot) \propto p(\theta_d \mid W, \tau_d) P(\tau_d)$$

The full conditional for θ *is*

$$\begin{aligned}
p(\theta \mid \tau,, \pi, y, X, W, Z, C) &\propto p(y \mid \theta, X, W, Z, C) p(\theta \mid W, \tau) \\
&= \prod_{j=1}^{J} \prod_{i:Z_i \in Z_j^*} p(y_i \mid X_i, Z_i, C_i, \theta_{C_i, Z_i},) p(\theta_{C_i Z_i} \mid \tau, W_j) \prod_{i:Z_i \in Z_j^{*C}} p(\theta_{C_i Z_i} \mid W_j, \tau) \\
&= \prod_{j=1}^{J} \left[\left(\prod_{k \in Z_j^*} p(\theta_{jk} \mid W_j, \tau) \prod_{i:Z_i \in Z_j^*} p(y_i \mid X_i, \theta_{jk}) \right) \left(\prod_{k \in Z_j^{*C}} p(\theta_{jk} \mid W_j, \tau) \right) \right]
\end{aligned}$$

Therefore, for all $j = 1, ..., J$ *and* $k = 1, ..., K$*, we have*

$$p(\theta_{jk} \mid \cdot) \propto \begin{cases} p(\theta_{jk} \mid W_j, \tau) \prod_{i:Z_i = k} p(y_i \mid X_i, \theta_{jk}) & , \textit{ if } k \in Z_j^* \\ p(\theta_{jk} \mid W_j, \tau) & , \textit{ if } k \in Z_j^{*C} \end{cases} \tag{A.1}$$

For the variable Z, the full conditional is given by

$$\begin{aligned} p(Z \mid \tau,\theta,\pi,y,X,W,C) &\propto p(y \mid \theta,Z,X,W,C)p(Z \mid \pi) \\ &= \prod_{i=1}^{n} p(y_i \mid \theta_{C_i Z_i},X_i,C_i,Z_i)p(Z_i \mid \pi) \end{aligned}$$

Therefore for all $i = 1,...,n$ we have

$$p(Z_i = k \mid \cdot) \propto \pi_k p(y_i \mid \theta_{C_i k},X_i,C_i)$$

or similarly

$$p(Z_i \mid \cdot) \propto \sum_{k=1}^{K} p_{ik} I(Z_i = k) \quad \ni \quad p_{ik} = \pi_k p(y_i \mid \theta_{C_i k},X_i,C_i) \tag{A.2}$$

Finally, for π the full conditional is

$$p(\pi \mid \tau,\theta,Z,y,X,W,C) \propto p(Z \mid \pi)p(\pi) = \prod_{i=1}^{n} p(Z_i \mid \pi)p(\pi)$$

Now, for simplicity, let $\pi \sim Dir(\alpha/K)$. The connection between this distribution and the stick-breaking process described in (A.6) can be found in Ishwaran and James (2001). Then we have

$$p(\pi \mid \tau,\theta,Z,y,X,W,C) \propto \prod_{i=1}^{n}\left(\prod_{k=1}^{K} \pi_k^{I(Z_i=k)}\right)\prod_{k+1}^{K}\pi_k^{\frac{\alpha}{K}-1} = \prod_{k=1}^{K}\pi_k^{N_k+\frac{\alpha}{K}-1}$$

Therefore,

$$p(\pi \mid \cdot) \propto Dir\left(N_1 + \frac{\alpha}{K},...,N_K + \frac{\alpha}{K}\right) \tag{A.3}$$

□

The proof of the proposition .2 is the following.

Proof 2 (Gibbs for hdpGLM with gaussian mixtures)**.** *Considering the results in proposition 1 and the model described in (1.16), we have the following. For τ, for each $d =$*

$1,...,D_x+1$

$$p(\tau_d \mid \cdot) \propto p(\beta_d \mid W,\tau_d)P(\tau_d) = \prod_{k=1}^{K}\left[\prod_{j=1}^{J} p(\beta_{dkj} \mid W,\tau_d)p(\tau_d)\right]$$

But by conjugacy of the gaussian distributions, we have

$$\prod_{j=1}^{J} p(\beta_{dkj} \mid W,\tau_d)p(\tau_d) \propto N_{D_w+1}(\mu_A^{(k)},\Sigma_A)$$

where

$$\begin{aligned} S_A &= \left(\Sigma_\tau^{-1}\sigma_\beta^2 + W^T W\right)^{-1} \\ \Sigma_A &= S_A\sigma_\beta^2 \\ \mu_k^{(k)} &= S_A W^T \beta_{dk} \end{aligned}$$

Therefore

$$p(\tau_d \mid \cdot) \propto \prod_{k=1}^{K} N_{D_w+1}(\mu_A^{(k)},\Sigma_A) \propto \exp\left\{-\frac{1}{2}\left[\tau_d^T(k\Sigma_A^{-1})\tau_d - 2\tau_d^T\Sigma_A^{-1}\left(\sum_{k=1}^{K}\mu_A^{(k)}\right)\right]\right\}$$

If we denote $\overline{\Sigma}_{\tau_d} = \frac{1}{K}\Sigma_A$ *and* $\overline{\mu}_{\tau_d} = \frac{1}{K}\sum_{k=1}^{K}\mu_A^{(k)}$ *then*

$$\tau_d \mid \cdot \propto N_{D_w+1}(\overline{\mu}_{\tau_d},\overline{\Sigma}_{\tau_d})$$

The full conditional for β *is*

$$\begin{aligned} p(\beta \mid \tau,\sigma^2,\pi,y,X,W,Z,C) &\propto p(y \mid \beta,\sigma^2,X,W,Z,C)p(\beta \mid W,\tau) \\ &= \prod_{j=1}^{J}\prod_{i:Z_i\in Z_j^*} p(y_i \mid X_i,Z_i,C_i,\beta_{C_i,Z_i},\sigma_{Z_i}^2)p(\beta_{C_iZ_i} \mid \tau,W_j)\prod_{i:Z_i\in Z_j^{*C}} p(\beta_{C_iZ_i} \mid W_j,\tau) \\ &= \prod_{j=1}^{J}\left[\left(\prod_{k\in Z_j^*} p(\beta_{jk} \mid W_j,\tau)\prod_{i:Z_i\in Z_j^*} p(y_i \mid X_i,\beta_{jk},\sigma_k^2)\right)\left(\prod_{k\in Z_j^{*C}} p(\beta_{jk} \mid W_j,\tau)\right)\right] \end{aligned}$$

Therefore, for all $j = 1,...,J$ and $k = 1,...,K$, we have

$$p(\beta_{jk} \mid \cdot) \propto \begin{cases} p(\beta_{jk} \mid W_j, \tau) \displaystyle\prod_{i:Z_i=k} p(y_i \mid X_i, \beta_{jk}, \sigma_k^2) & , \text{ if } k \in Z_j^* \\ p(\beta_{jk} \mid W_j, \tau) & , \text{ if } k \in Z_j^{*C} \end{cases} \tag{A.4}$$

Denote $X_{kj} = \left\{X_i \,\middle|\, C_i = j, Z_i = k\right\}$, $y_{kj} = \left\{y_i \,\middle|\, C_i = j, Z_i = k\right\}$, it is clear from (A.4), (1.16), and the conjugacy of the normal distribution that for $k \in Z_j^*$

$$\beta_{jk} \mid \cdot \propto N_{D_x+1}(\bar{\mu}_\beta, \bar{\Sigma}_\beta) \qquad \text{where} \qquad S_\beta = \left(\Sigma_\beta^{-1}\sigma_k^2 + X_{kj}^T X_{kj}\right)^{-1} \quad , \quad \bar{\Sigma}_\beta = S_\beta \sigma_k^2$$
$$\bar{\mu}_\beta = S_\beta \left[\Sigma_\beta^{-1}(W_j^T \tau)^T + \frac{X_{kj}^T y_{kj}}{\sigma_k^2}\right] \sigma_k^2$$

The full conditional for σ^2 is

$$\begin{aligned} p(\sigma^2 \mid \tau, \beta, \pi, Z, y, X, W, C) &\propto p(y \mid \beta, \sigma^2, Z, X, W, C) p(\sigma^2) \\ &= \prod_{i=1}^{n} p(y_i \mid \beta_{C_i Z_i}, \sigma_{Z_i}^2, X_i, Z_i, C_i) p(\sigma_{Z_i}^2) \\ &= \left(\prod_{k \in Z^*} p(\sigma_k^2) \prod_{i:Z_i=k} p(y_i \mid \beta_{C_i k}, X_i, C_i)\right) \left(\prod_{k \in Z^{*C}} p(\sigma_k^2)\right) \end{aligned}$$

Therefore, for all $k = 1,...,K$ we have

$$p(\sigma_k^2 \mid \cdot) \propto \begin{cases} p(\sigma_k^2) \displaystyle\prod_{i:Z_i=k} p(y_i \mid \beta_{C_i k}, X_i, C_i) & , \text{ if } k \in Z^* \\ p(\sigma_k^2) & , \text{ if } k \in Z^{*C} \end{cases} \tag{A.5}$$

Given the full conditional of σ^2 in (A.5), the distributions in (1.16), and the fact that the scaled inverse χ^2 distribution is a conjugate prior for a gaussian likelihood with known mean, which is the case for the full conditional, it is straightforward to see that for $k \in Z^*$, $X_k = \left\{X_i \,\middle|\, Z_i = k\right\}$, and $y_k = \left\{y_k \,\middle|\, Z_i = k\right\}$

$$\sigma_k^2 \mid \cdot \propto \textit{Scale-inv-}\chi^2(\bar{\nu}, \bar{s}^2) \quad \text{where} \quad \bar{\nu} = \nu + N_k \quad , \quad \bar{s}^2 = \frac{\nu s^2 + N_k \hat{s}^2}{\nu + N_k} \quad ,$$
$$\hat{s}^2 = \frac{1}{N_k}(y_k - X_k \beta_k)^T (y_k - X_k \beta_k)$$

The full conditionals for Z and π are as in (A.2) and (A.3), respectively.

$\square$

A.2 Riemann Manifold Hamiltonian Monte Carlo

The proposed model from which we derive the RMHMC within Gibbs is defined as follows

$$
\begin{aligned}
V_l \mid \alpha_o &\sim \mathrm{Beta}(1, \alpha_o) \\
\pi_k &= \begin{cases} V_1 & , k = 1 \\ V_k \prod_{l=1}^{k-1} (1 - V_l) & , k > 1 \end{cases} \\
Z_i \mid \pi &\sim \mathrm{Cat}(\pi) && , \pi \in \Delta^{\infty} \\
\tau_d &\sim p(\tau_d) && , d = 1, \ldots, D_x + 1 \\
\theta_{kj} \mid Z_{ik}, \tau, C_{ij}, W &\sim p(\theta_{jk} \mid W, \tau) && , j = 1, \ldots, J \\
y_i \mid Z_{ik}, \theta_{kj}, X_i, C_{ij} &\sim p(y_i \mid Z_{ik}, X_i, \theta_{kj}) && \ni \quad \mathbb{E}[y_i \mid Z_{ik}, \theta_{kj}, X_i, C_{ij}] = g^{-1}(X_i^T \theta_{kj}) \\
& && \quad\;\; p(y_i \mid Z_{ik}, X_i, \theta_{kj}) \text{ from exponential family}
\end{aligned}
\tag{A.6}
$$

As discussed in the main paper, when the outcome variable y_i in the model (A.6) is binomial or multinomial distributed the Gibbs sampler developed in the paper cannot be used anymore for the parameters θ (or β). We use a RMHMC update within Gibbs to sample the β coefficients in these cases. The random variable of interest is $\beta_{kj} \in \mathbb{R}^{D+x+1}$ and we use $v \in \mathbb{R}^{D_x+1}$ as the ancillary variable (momentum) such that $v \sim N_{D_x+1}(0, G(\beta_{kj}))$. The Hamiltonian is defined by

$$
\begin{aligned}
H(\beta_{kj}, v) = U(\beta_{kj}, v) + K(\beta_{kj}, v) = -\,(\beta_{kj} \mid \cdot) + \frac{D_x + 1}{2} \ln(2\pi) \\
+ \frac{1}{2}\left[\ln\left(\det[G(\beta_{kj})]\right) + v^T G(\beta_{kj})^{-1} v\right]
\end{aligned}
\tag{A.7}
$$

whose solution is

$$
\begin{aligned}
\nabla_v H(\beta_{kj}, v) &= G(\beta_{kj})^{-1} v \\
\nabla_{\beta_{kj}} H(\beta_{kj}, v) &= -\Big[\nabla_{\beta_{kj}} U(\beta_{kj}, v) - \frac{1}{2} \operatorname{tr}\left\{ G(\beta_{kj})^{-1} \nabla_{\beta_{kj}} G(\beta_{kj}) \right\} \\
&\qquad + \frac{1}{2} \left(v^T G(\beta_{kj})^{-1} G(\beta_{kj})^{-1} v \right) \nabla_{\beta_{kj}} G(\beta_{kj}) \Big]
\end{aligned}
\tag{A.8}
$$

The Hamiltonian equations are solved using the generalized Stormer-Verlet leapfrog integrator (Calin and Chang, 2006; Girolami and Calderhead, 2011). So for L leapfrog steps with size ε, and $l = 1, \ldots L$, we have

$$
\begin{aligned}
v^{l+\frac{\varepsilon}{2}} &= v^l - \frac{\varepsilon}{2} \nabla_{\beta_{kj}} H\left(\beta_{kj}^l, v^{l+\frac{\varepsilon}{2}}\right) \\
\beta_{kj}^{l+\varepsilon} &= \beta_{kj}^l + \frac{\varepsilon}{2} \left[\nabla_v H\left(\beta_{kj}^l, v^{l+\frac{\varepsilon}{2}}\right) + \nabla_v H\left(\beta_{kj}^{l+\varepsilon}, v^{l+\frac{\varepsilon}{2}}\right) \right] \\
v^{l+\varepsilon} &= v^{l+\frac{\varepsilon}{2}} - \frac{\varepsilon}{2} \nabla_{\beta_{kj}} H\left(\beta_{kj}^{l+\varepsilon}, v^{l+\frac{\varepsilon}{2}}\right)
\end{aligned}
\tag{A.9}
$$

When y_i is binomial, that is, the distribution of y_i is defined by

$$
y_i \sim \operatorname{Bin}(p_{kj}) \quad , \quad p_{kj} = \frac{1}{1 + e^{-X_i^T \beta_{kj}}}
$$

then the elements of the RMHMC for the model when $k \in Z_j^*$ are defined by the following equations:

$$
\begin{aligned}
U(\beta_{kj}) = -\ln p(\beta_{kj} \mid \cdot) \propto -\Big[&- \frac{D_x + 1}{2} \ln 2\pi - \frac{1}{2} \ln(\det(\Sigma_\beta)) \\
&- \frac{1}{2} (\beta_{kj} - (W_j^T \tau)^T)^T \Sigma_\beta^{-1} (\beta_{kj} - (W_j^T \tau)^T) \\
&- \sum_{i \in I_k} y_i \ln\left(1 + e^{-X_i^T \beta_{kj}}\right) - \sum_{i \in I_k} (1 - y_i) \ln\left(1 + e^{X_i^T \beta_{kj}}\right) \Big] \\
\nabla_{\beta_{kj}} U(\beta_{kj}) = -\Big[&- (\beta_{kj} - (W_j^T \tau)^T)^T \Sigma_\beta^{-1} + \sum_{i \in I_k} X_i y_i p(y_i = 0 \mid \cdot) - \sum_{i \in i_k} X_i (1 - y_i) p(y_i = 1 \mid \cdot) \Big]
\end{aligned}
$$

In practice we use $G(\beta_{kj}) = I_{(D_x+1)\times(D_x+1)}$, which is the most widely used approach in applications (Neal et al., 2011; Liu, 2008). It also simplify the equation (A.7), (A.8), and (A.9). Using $v \sim N_{D_x+1}(0, I)$, the integrator reduces to the standard Stormer-Verlet leapfrog integrator (Duane et al., 1987; Neal et al., 2011) and we have the following equations for the hdpGLM:

$$\begin{aligned}
\nabla_{\beta_{kj}} H(\beta_{kj}, v) &= \nabla_{\beta_{kj}} U(\beta_{kj}) - v \\
v^{l+\frac{\varepsilon}{2}} &= v^{l} - \frac{\varepsilon}{2}\nabla_{\beta_{kj}} U(\beta_{kj}) \\
\beta_{kj}^{l+\varepsilon} &= \beta_{kj}^{l} + \varepsilon v^{l+\frac{\varepsilon}{2}} \\
v^{l+\varepsilon} &= v^{l+\frac{\varepsilon}{2}} - \frac{\varepsilon}{2}\nabla_{\beta_{kj}} U(\beta_{kj})
\end{aligned}$$

With these definitions, the RMHMC is presented in the algorithm 3.

Algorithm 3 Riemman Manifold Hamiltonian Monte Carlo

Require: $Z^{(t)}, \beta^{(t)}, \pi^{(t)}, \tau^{(t)}$

for $j = 1, \ldots, J$ and for $k \in Z_j^*$ **do**
    sample $v^{\text{current}} \sim N_{D_x+1}(0, G(\beta_{kj}))$
    Let $v \leftarrow v^{\text{current}}, \beta_{kj} \leftarrow \beta_{kj}^{(t)}$
    Set $v \leftarrow v - \frac{\varepsilon}{2} \nabla_{\beta_{kj}} U(\beta_{kj})$
    for $l = L - 1$ **do**
        $\beta_{kj} \leftarrow \beta_{kj} + \varepsilon \left(G^{-1}(\beta_{kj}) v \right)$
        $v \leftarrow v - \frac{\varepsilon}{2} \nabla_{\beta_{kj}} U(\beta_{kj})$
    end for
    Set $v \leftarrow v - \frac{\varepsilon}{2} \nabla_{\beta_{kj}} U(\beta_{kj})$
    Set $v = -v$
    sample $u \sim U(0,1)$
    if $u < \min \left\{ 1, \exp \left\{ -H(\beta_{kj}, v) + H(\beta_{kj}^{(t)}, v^{\text{current}}) \right\} \right\}$ **then**
        $\beta_{kj}^{(t+1)} \leftarrow \beta_{kj}$
    else
        $\beta_{kj}^{(t+1)} \leftarrow \beta_{kj}^{(t)}$
    end if
end for

A.3 Prior Perturbation Analysis

This section evaluates the effect of prior perturbations on three quantities: ”bias” (the distance between the estimated posterior expectation and the true), the size of the 95% HPD intervals, and the estimated number of clusters.

As mentioned in the main paper, the MC exercises were conducted using the following prior parameters: $(\mu_{\tau_d}, \sigma_{\tau_d} I, \sigma_{\beta_{kj}} I, s^2, \nu, \alpha_0) = (0, 10I, 10I, 10, 10, 1)$, where I represents the identity matrix. The choice of those values was based on experimentation. To evaluate the effect of prior perturbation, I estimated the model 1215 times, each time using a different combination of the prior parameter whose values were selected from the set described in the following table:

Prior parameters	Set of values
α	$\{.5, 1, 5\}$
s^2	$\{1, 4, 10\}$
ν	$\{1, 4, 10\}$
σ_τ	$\{1, 5, 10\}$
σ_β	$\{1, 5, 10\}$
n (sample size)	$\{500, 1000, 2000, 5000, 10000\}$

I used the same setting with three clusters and three covariates for all estimations under different prior combinations to properly compare the effect of prior perturbation. The Gibbs sampler ran for 17000 iterations, and the last 7000 were recorded.

The results are summarized in Tables A.1 to A.3 and Figure A.1. Table A.1 shows summaries of how the "bias" is affected by the prior specification. For each sample size n, the upper half of the table shows the prior setting containing the linear coefficient β that produced the maximum absolute value of the bias. The last column of the upper half shows the average bias computed across prior combinations and linear coefficients. The bottom half of the table shows the same two measures - the maximum absolute value of the bias and the average bias - for each sample size, but considering only the benchmark with prior parameter as used in the MC exercises. Table A.2 displays similar information but with consequences of the prior selection on the 95% HPD intervals. Table A.3 compares the estimated number of clusters in the worst case (more distance from the true) against the priors used in the MC study. Finally, Figure A.1 shows the number of clusters, the bias, and the sizes of the 95% HPD intervals for all prior combinations and sample sizes. In the upper half of the figure, the dots represent the number of clusters activated in each estimation. In the bottom-left, the dots represent the bias of each linear coefficient β, and in the bottom right, the dots represent the size of the 95% HPD interval, also for each linear coefficient. Red lines in the figure show the average values.

We can see from the tables and the figure that the estimation is not very sensitive on average to the choice of those prior parameters in the range considered here, but for certain combinations, in the worst case, the model can demand very large data sets to escape the influence of the prior specification. This is true specially for extreme values of the concentration parameter α and values that produce highly dispersed inverse-scaled-χ^2 distribution, which can be generated by low values (below five) of the scale parameter s^2.

In particular, the estimated number of clusters can be sensitive to α. That is expected and it is a feature of models using DPP. In Dirichlet processes, large values of α tend to

Table A.1: Sensitivity of estimated bias ($\beta - \hat{\mathbb{E}}[\beta \mid \cdot]$) to prior specification: worst case versus priors used in the main MC study

Sample size	Priors: (α, s^2, ν, σ_β)	Absolute Maximum Estimated Bias	Average Estimated Bias
Worst Case (average computed across priors and linear coefficients)			
500	(5,1,4,5)	9.2910	0.0665
1000	(0.5,1,10,5)	8.5466	-0.1051
2000	(0.5,4,1,10)	8.3330	-0.2286
5000	(0.5,4,10,5)	7.7365	-0.0364
10000	(5,4,4,10)	8.0995	0.0255
Values used in the main MC study (average computed across linear coefficients)			
500	(1,10,10,10)	0.1531	0.0115
1000	(1,10,10,10)	0.1647	-0.0520
2000	(1,10,10,10)	0.0800	0.0053
5000	(1,10,10,10)	0.0657	-0.0020
10000	(1,10,10,10)	0.2383	0.0043

Table A.2: Sensitivity of the size of the 95% HPD interval to prior specification: worst case versus priors used in the main MC study

Sample size	Priors: (α, s^2, ν, σ_β)	Maximum size of the 95% HPD intervals	Mean size of the 95% HPD intervals
Worst Case (average computed across priors and linear coefficients)			
500	(0.5,1,1,10)	15.7945	3.7669
1000	(0.5,1,1,10)	12.9130	3.2080
2000	(5,1,1,1)	14.6177	3.4737
5000	(1,1,1,5)	13.0680	2.5827
10000	(5,1,1,5)	14.7897	2.0746
Values used in the main MC study (average computed across linear coefficients)			
500	(1,10,10,10)	0.4253	0.3785
1000	(1,10,10,10)	0.2747	0.2509
2000	(1,10,10,10)	0.1724	0.1651
5000	(1,10,10,10)	0.1159	0.1087
10000	(1,10,10,10)	1.5535	0.8132

Table A.3: Sensitivity of estimated number of clusters to prior specification: worst case versus priors used in the main MC study

Sample size	Priors: (α, s^2, ν, σ_β)	K estimated	Mean across different priors	Percentage equal to true across different priors
Worst Case				
500	(5,1,1,10)	21	4.740741	66.67 %
1000	(5,1,1,5)	20	5.654321	66.67 %
2000	(5,1,1,10)	43	5.530864	72.84 %
5000	(1,1,1,5)	60	10.246914	55.56 %
10000	(5,1,1,5)	88	12.913580	59.26 %
Values used in the main MC study				
500	(1,10,10,10)	3	–	– %
1000	(1,10,10,10)	3	–	– %
2000	(1,10,10,10)	3	–	– %
5000	(1,10,10,10)	3	–	– %
10000	(1,10,10,10)	8	–	– %

produce large number of clusters. Antoniak (1974) has shown that for any sample size n, $\mathbb{E}[K \mid n,\alpha] = \sum_{i=1}^{n} \frac{\alpha}{\alpha+i-1}$, where K denotes a random variable that captures the number of clusters in n observations from a Dirichlet process model with concentration parameter α. So it is clear that $\mathbb{E}[K \mid n,\alpha] \to n$ if $\alpha \to \infty$, and $\mathbb{E}[K \mid n,\alpha] \to 0$ it $\alpha \to 0$. Table A.4 shows $\mathbb{E}[K \mid n,\alpha]$ for the values of α and n used in this section. The table shows the expectation of K if the DPP was the true and K was a random variable denoting the number of clusters. Note that those are not posterior expectations, but the expectation of the number of clusters when DPP is actually the acronym-next-pages. When K is finite, fixed, but unknown, the results presented here and in the main paper shows that DPP can be used to approximate the true unknown finite mixture model, that K can be estimated as a result, that on average the estimation produces good approximation, but that in the worst case it can be affected by choice of α. A much larger chain and large data set may be needed for extreme values of α.

In all the simulated data sets and discussions in the paper, K is fixed but unknown, and we approximate it using the hierarchical DPP model. For all estimations I selected a fixed value for the concentration parameter: $\alpha = 1$. Using a fixed value for α reduces the computational cost of the Monte Carlo study substantially, and it also supported the derivation of the full Gibbs as presented in the paper. The results in the paper and this section indicate that $\alpha = 1$ is a sensible choice. The benchmark values in the MC exercises have shown good results in a variety of data sets and parameter values. It is important to keep in mind, however, that such choice may not be appropriate for all data sets. If

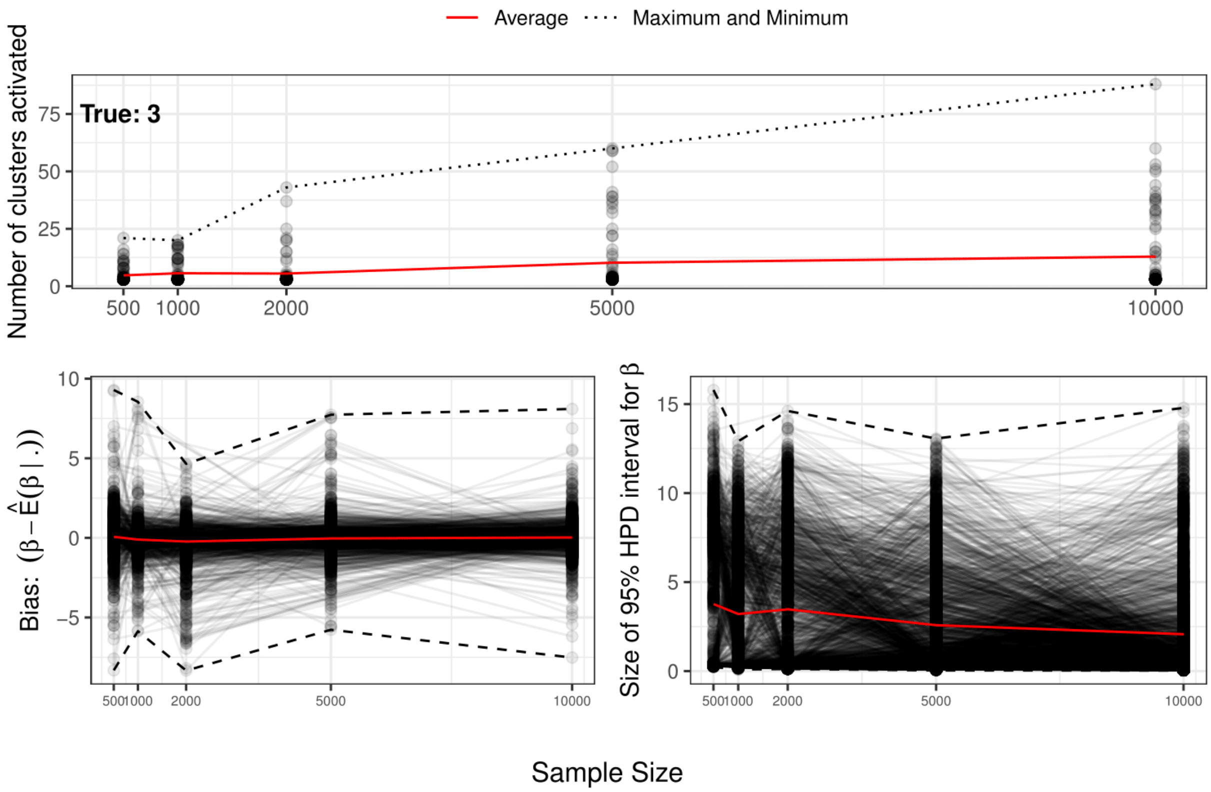


Figure A.1: Sensitivity of number of clusters, bias $(\beta - \mathbb{E}[\beta \mid \cdot])$, and 95% HPD interval for different sample sizes and prior parameters

the chain is taken too long to display good convergence diagnostics or multiple estimations seems to be generating different results, practitioners can adjust α and the other fixed parameters to reflect their prior beliefs about α. It may be advisable also centering and scaling the data to estimate effects of covariates in terms of standard deviation of covariates (see Rossi (2014) for similar recommendations).

The model can be extended to incorporate prior uncertainty on α. Some authors have proposed models with Gamma priors on α (West, Muller and Escobar, 1994; Mukhopadhyay and Gelfand, 1997; Gelfand, Kottas and MacEachern, 2005). The difficulty then becomes to select priors for that distribution, which can impact on the posterior distribution of α. In those approaches, learning about that parameter can be difficult, and it may require large data sets. For that reason, Dorazio (2009) proposes a prior selection procedure based on minimizing a Kullback-Leibler divergence computed with the prior distribution of the number of clusters K induced by the prior on α and a ancillary distribution on $K = 1, \ldots, n$ that can capture our uncertainty about K. The model can be extended in those

Table A.4: Prior Expectation of the number of clusters for different sample sizes (n) and values of the concentration parameter α

α	Sample size (n)	$E[K \mid n, \alpha]$
0.5	500	4.0891
0.5	1000	4.4356
0.5	2000	4.7822
0.5	5000	5.2404
0.5	10000	5.5869
1.0	500	6.7928
1.0	1000	7.4855
1.0	2000	8.1784
1.0	5000	9.0945
1.0	10000	9.7876
5.0	500	23.5873
5.0	1000	27.0306
5.0	2000	30.4852
5.0	5000	35.0599
5.0	10000	38.5234

directions, although it will increase the computational cost for the estimation.

A.4 Details of the Simulation Study

This section presents some details of the simulation study, the extension of the exercise from 100 to 1000 replications, and the tables with the MC error. Details of the prior parametrization are in the section A.3. The MCMC ran until the MCMC error was below 0.05 for all parameters (Flegal, 2008; Gong and Flegal, 2015)

Table A.5 displays the summary statistics of the MC error for the simulation study presented in the main paper. Note that the average value of the MC error is quite small, as well as the maximum value. That is true for all parameter sets. Table A.6 shows the estimated posterior expectation, the MC error, and the true value for each β in each cluster and each parameter set. We can see that the MC errors are in general small and the estimated values very close to the true values.

Table A.6: True, Monte Carlo error, and posterior expectation of each β per parameter set and cluster

		Cluster									
Parameter	Estimate	1	2	3	4	5	6	7	8	9	10
Parameter Set 1 (N. of Clusters: 7; N. of Covariates: 4)											
β_1	True	2.8461	-0.2693	4.5358	4.9792	-4.3710	7.9719	-2.8122	–	–	–
β_1	MCMC Mean	2.8340	-0.2810	4.2452	4.9691	-4.3731	7.9653	-2.8170	–	–	–
β_1	MCMC error	0.0513	0.0505	1.0963	0.0464	0.0428	0.0452	0.0456	–	–	–
β_2	True	0.4319	1.1724	6.6526	-4.4481	1.8016	8.1086	-9.1892	–	–	–
β_2	MCMC Mean	0.4258	1.1740	6.2130	-4.4441	1.7929	8.1082	-9.1888	–	–	–
β_2	MCMC error	0.0471	0.0384	1.6139	0.0472	0.0502	0.0458	0.0458	–	–	–
β_3	True	-6.4458	9.7919	-3.3883	3.8350	-3.3731	8.4948	-6.7871	–	–	–
β_3	MCMC Mean	-6.4347	9.7833	-3.1728	3.8333	-3.3793	8.4908	-6.7782	–	–	–
β_3	MCMC error	0.0444	0.0473	0.8053	0.0439	0.0481	0.0528	0.0466	–	–	–
β_4	True	-9.4002	4.0393	-4.1365	2.8764	-5.6639	-6.9705	-0.2020	–	–	–
β_4	MCMC Mean	-9.3907	4.0328	-3.8762	2.8833	-5.6537	-6.9739	-0.2108	–	–	–
β_4	MCMC error	0.0525	0.0458	0.9850	0.0436	0.0499	0.0505	0.0479	–	–	–
β_5	True	5.4716	6.6912	-3.8207	-9.5771	9.7805	3.3063	-6.9065	–	–	–
β_5	MCMC Mean	5.4706	6.6822	-3.5633	-9.5764	9.7745	3.3096	-6.9055	–	–	–
β_5	MCMC error	0.0563	0.0461	0.9658	0.0444	0.0495	0.0457	0.0497	–	–	–
Parameter Set 2 (N. of Clusters: 5; N. of Covariates: 3)											
β_1	True	9.1445	-6.0408	-8.7230	2.2769	-1.7914	–	–	–	–	–
β_1	MCMC Mean	9.1411	-6.0349	-8.7143	2.2665	-1.7694	–	–	–	–	–
β_1	MCMC error	0.0413	0.0417	0.0411	0.0462	0.1481	–	–	–	–	–
β_2	True	-4.1189	6.0930	-7.7552	-7.8354	-3.8545	–	–	–	–	–
β_2	MCMC Mean	-4.1114	6.0878	-7.7426	-7.8315	-3.8024	–	–	–	–	–
β_2	MCMC error	0.0379	0.0393	0.0389	0.0413	0.3828	–	–	–	–	–
β_3	True	-9.5885	-9.8816	-4.8716	5.4633	8.1354	–	–	–	–	–
β_3	MCMC Mean	-9.5946	-9.8767	-4.8742	5.4583	8.0071	–	–	–	–	–
β_3	MCMC error	0.0434	0.0379	0.0388	0.0437	0.8725	–	–	–	–	–
β_4	True	4.9159	7.8931	8.7228	9.0426	-4.3706	–	–	–	–	–
β_4	MCMC Mean	4.9136	7.8858	8.7227	9.0325	-4.2889	–	–	–	–	–

Table A.6: True, Monte Carlo error, and posterior expectation of each β per parameter set and cluster *(continued)*

		Cluster									
Parameter	Estimate	1	2	3	4	5	6	7	8	9	10
β_4	MCMC error	0.0420	0.0462	0.0473	0.0419	0.4999	–	–	–	–	–
Parameter Set 3 (N. of Clusters: 4; N. of Covariates: 3)											
β_1	True	2.1420	-3.2250	-5.9593	5.7489	–	–	–	–	–	–
β_1	MCMC Mean	1.8353	-3.2095	-5.9560	5.7361	–	–	–	–	–	–
β_1	MCMC error	0.7418	0.0743	0.0479	0.0471	–	–	–	–	–	–
β_2	True	-2.2197	-1.6789	-4.9497	-8.0287	–	–	–	–	–	–
β_2	MCMC Mean	-2.0263	-1.6679	-4.9482	-8.0293	–	–	–	–	–	–
β_2	MCMC error	0.4735	0.0439	0.0389	0.0431	–	–	–	–	–	–
β_3	True	-2.3680	-5.3547	4.6992	-5.3455	–	–	–	–	–	–
β_3	MCMC Mean	-2.1589	-5.3479	4.7003	-5.3371	–	–	–	–	–	–
β_3	MCMC error	0.4878	0.0847	0.0401	0.0411	–	–	–	–	–	–
β_4	True	-0.5086	-0.3742	7.8034	7.7347	–	–	–	–	–	–
β_4	MCMC Mean	-0.4262	-0.3669	7.8005	7.7390	–	–	–	–	–	–
β_4	MCMC error	0.2304	0.0459	0.0460	0.0392	–	–	–	–	–	–
Parameter Set 4 (N. of Clusters: 10; N. of Covariates: 3)											
β_1	True	6.4346	8.6388	-7.1063	-0.5870	7.9331	-4.6517	8.7052	-2.8011	3.6076	4.1293
β_1	MCMC Mean	6.4254	8.6307	-7.1046	-0.4646	–	-4.6518	8.7140	-2.7246	3.5984	3.9971
β_1	MCMC error	0.0632	0.0562	0.0537	0.2964	–	0.0583	0.0595	0.3052	0.0938	0.3760
β_2	True	-2.6849	8.7468	9.8020	1.9841	-4.0242	-9.8518	-2.7650	-0.6405	7.9583	-4.3867
β_2	MCMC Mean	-2.6908	8.7506	9.7952	1.7767	–	-9.8542	-2.7652	-0.6221	7.9330	-4.1721
β_2	MCMC error	0.0610	0.0527	0.0515	0.4119	–	0.0449	0.0588	0.1044	0.2131	0.4874
β_3	True	-5.5527	1.6805	6.3605	2.7285	-1.0697	4.8846	-6.6493	4.5761	0.5479	1.6996
β_3	MCMC Mean	-5.5470	1.6855	6.3594	2.4642	–	4.8889	-6.6377	4.4818	0.5594	1.6212
β_3	MCMC error	0.0564	0.0526	0.0530	0.5743	–	0.0528	0.0586	0.3773	0.0648	0.2616
β_4	True	8.6219	-7.7376	-0.5569	2.6615	2.6063	5.7916	1.3942	-8.9141	-1.4563	0.6422
β_4	MCMC Mean	8.6174	-7.7381	-0.5505	2.3886	–	5.7896	1.3884	-8.7106	-1.4624	0.6404
β_4	MCMC error	0.0556	0.0574	0.0468	0.5946	–	0.0491	0.0605	0.8134	0.0696	0.1417
Parameter Set 5 (N. of Clusters: 7; N. of Covariates: 5)											
β_1	True	-3.7746	-5.4668	-7.6802	1.1977	5.9336	-0.2147	-6.1483	–	–	–
β_1	MCMC Mean	-3.7702	-5.4786	-7.6816	1.1949	5.9273	-0.2204	-6.1439	–	–	–
β_1	MCMC error	0.0533	0.0662	0.0466	0.0588	0.0426	0.0731	0.0468	–	–	–
β_2	True	-1.2831	-7.8355	-6.5404	-0.3373	-7.0447	-6.2112	8.5538	–	–	–
β_2	MCMC Mean	-1.2776	-7.8253	-6.5314	-0.3387	-7.0344	-5.7822	8.5433	–	–	–
β_2	MCMC error	0.0512	0.0463	0.0457	0.0467	0.0521	1.4820	0.0440	–	–	–
β_3	True	-1.3126	-8.3251	4.5719	-6.6823	0.0608	-1.0889	-6.4825	–	–	–
β_3	MCMC Mean	-1.3157	-8.3086	4.5622	-6.6700	0.0616	-1.0417	-6.4765	–	–	–
β_3	MCMC error	0.0525	0.0549	0.0471	0.0459	0.0379	0.1973	0.0474	–	–	–
β_4	True	-3.0599	-9.7882	-9.0171	-8.2836	6.8602	-2.4649	4.5642	–	–	–
β_4	MCMC Mean	-3.0467	-9.7698	-9.0050	-8.2824	6.8634	-2.3245	4.5694	–	–	–
β_4	MCMC error	0.0607	0.0544	0.0376	0.0507	0.0470	0.5041	0.0473	–	–	–
β_5	True	6.6265	3.6617	-3.4436	3.7347	7.0128	0.4728	6.0935	–	–	–
β_5	MCMC Mean	6.6150	3.6623	-3.4362	3.7322	7.0067	0.4606	6.0952	–	–	–
β_5	MCMC error	0.0510	0.0477	0.0513	0.0545	0.0497	0.0741	0.0486	–	–	–
β_6	True	5.6638	1.5949	6.4922	-3.5569	-1.2739	1.9962	-9.9017	–	–	–
β_6	MCMC Mean	5.6558	1.5807	6.4879	-3.5475	-1.2793	1.8697	-9.8919	–	–	–
β_6	MCMC error	0.0591	0.0623	0.0511	0.0489	0.0493	0.4384	0.0473	–	–	–
Parameter Set 6 (N. of Clusters: 1; N. of Covariates: 0)											

Table A.6: True, Monte Carlo error, and posterior expectation of each β per parameter set and cluster *(continued)*

		Cluster									
Parameter	Estimate	1	2	3	4	5	6	7	8	9	10
β_1	True	-0.1968	–	–	–	–	–	–	–	–	–
β_1	MCMC Mean	-0.2171	–	–	–	–	–	–	–	–	–
β_1	MCMC error	0.1673	–	–	–	–	–	–	–	–	–
Parameter Set 7 (N. of Clusters: 4; N. of Covariates: 2)											
β_1	True	3.3510	5.5764	7.1851	-5.8302	–	–	–	–	–	–
β_1	MCMC Mean	3.3476	5.5469	7.1918	-5.3099	–	–	–	–	–	–
β_1	MCMC error	0.0994	0.2005	0.0372	1.5248	–	–	–	–	–	–
β_2	True	-4.3097	2.9101	7.9174	4.1559	–	–	–	–	–	–
β_2	MCMC Mean	-4.2880	2.8864	7.9131	3.8197	–	–	–	–	–	–
β_2	MCMC error	0.1681	0.1204	0.0384	0.9978	–	–	–	–	–	–
β_3	True	-9.4016	-6.3153	4.9380	-3.4102	–	–	–	–	–	–
β_3	MCMC Mean	-9.3762	-6.2819	4.9363	-3.1650	–	–	–	–	–	–
β_3	MCMC error	0.2617	0.2057	0.0404	0.7669	–	–	–	–	–	–
Parameter Set 8 (N. of Clusters: 2; N. of Covariates: 5)											
β_1	True	5.6029	6.0953	–	–	–	–	–	–	–	–
β_1	MCMC Mean	5.6057	5.8913	–	–	–	–	–	–	–	–
β_1	MCMC error	0.0365	1.0385	–	–	–	–	–	–	–	–
β_2	True	3.7438	-5.3878	–	–	–	–	–	–	–	–
β_2	MCMC Mean	3.7405	-5.1924	–	–	–	–	–	–	–	–
β_2	MCMC error	0.0344	0.9935	–	–	–	–	–	–	–	–
β_3	True	-3.4657	1.3461	–	–	–	–	–	–	–	–
β_3	MCMC Mean	-3.4630	1.2993	–	–	–	–	–	–	–	–
β_3	MCMC error	0.0366	0.2394	–	–	–	–	–	–	–	–
β_4	True	-9.3687	-1.4674	–	–	–	–	–	–	–	–
β_4	MCMC Mean	-9.3684	-1.4309	–	–	–	–	–	–	–	–
β_4	MCMC error	0.0390	0.2103	–	–	–	–	–	–	–	–
β_5	True	3.0410	3.6361	–	–	–	–	–	–	–	–
β_5	MCMC Mean	3.0409	3.5077	–	–	–	–	–	–	–	–
β_5	MCMC error	0.0325	0.6258	–	–	–	–	–	–	–	–
β_6	True	-3.5824	-7.7044	–	–	–	–	–	–	–	–
β_6	MCMC Mean	-3.5858	-7.4373	–	–	–	–	–	–	–	–
β_6	MCMC error	0.0347	1.3367	–	–	–	–	–	–	–	–
Parameter Set 9 (N. of Clusters: 10; N. of Covariates: 2)											
β_1	True	-8.0023	7.2055	5.0725	-8.2809	-8.7811	4.2359	-9.9581	2.4104	-3.1409	-0.7061
β_1	MCMC Mean	-7.9718	6.8629	–	-8.0508	-8.7664	4.1149	-9.9473	2.3620	-2.9757	-0.5916
β_1	MCMC error	0.2386	0.7669	–	0.7421	0.2083	0.4606	0.0578	0.2952	0.3749	0.3023
β_2	True	8.0038	0.9477	3.5049	-5.4635	7.8988	9.4809	-3.3568	5.0702	-3.6214	2.0435
β_2	MCMC Mean	7.9600	0.9294	–	-5.2767	7.8755	9.2670	-3.3558	4.8840	-3.4042	1.7063
β_2	MCMC error	0.2188	0.0927	–	0.5682	0.1650	0.7722	0.0534	0.5710	0.4900	0.5177
β_3	True	5.3229	1.7302	-8.6640	-1.1130	-3.8013	1.9706	-8.7511	-7.4686	6.7933	3.5699
β_3	MCMC Mean	5.2997	1.6535	–	-1.0755	-3.7790	1.9068	-8.7519	-7.1621	6.4443	2.8895
β_3	MCMC error	0.1487	0.1612	–	0.1376	0.1766	0.2024	0.0584	0.8681	0.7768	0.9490
Parameter Set 10 (N. of Clusters: 3; N. of Covariates: 2)											
β_1	True	0.0924	0.1113	-7.4930	–	–	–	–	–	–	–
β_1	MCMC Mean	0.0387	0.1130	-7.4726	–	–	–	–	–	–	–
β_1	MCMC error	0.1826	0.0490	0.1489	–	–	–	–	–	–	–
β_2	True	3.6043	-6.8301	6.8375	–	–	–	–	–	–	–

Table A.6: True, Monte Carlo error, and posterior expectation of each β per parameter set and cluster *(continued)*

		Cluster									
Parameter	Estimate	1	2	3	4	5	6	7	8	9	10
β_2	MCMC Mean	3.2693	-6.7974	6.8269	–	–	–	–	–	–	–
β_2	MCMC error	0.8220	0.2302	0.1298	–	–	–	–	–	–	–
β_3	True	2.6229	6.4300	-1.2320	–	–	–	–	–	–	–
β_3	MCMC Mean	2.4522	6.4049	-1.2277	–	–	–	–	–	–	–
β_3	MCMC error	0.4166	0.1980	0.0546	–	–	–	–	–	–	–

Table A.7 shows values of the MC study using 1000 simulations for two parameter sets. As we can see, the number of estimated clusters, coverage, and HPD intervals are reinforced the results of the MC exercise with 100 replications for ten different parameter sets. The same is true for the MC error displayed in tables A.8 and A.9.

Table A.9: True, MC error, and posterior expectation of eacn β per parameter set and cluster

		Cluster				
Parameter	Estimate	1	2	3	4	5
Parameter Set 1 (N. of Clusters: 5; N. of Covariates: 1)						
β_1	True	-9.7860	-6.5590	-5.0161	3.2058	1.8956
β_1	MCMC Mean	-9.6749	–	-4.7423	2.3554	–
β_1	MCMC error	0.4887	–	0.6616	0.9238	–
β_2	True	-3.0997	8.9872	4.6558	1.6063	7.3254
β_2	MCMC Mean	-3.0461	–	4.5645	1.7286	–
β_2	MCMC error	0.2578	–	0.5309	0.3695	–
Parameter Set 2 (N. of Clusters: 3; N. of Covariates: 4)						
β_1	True	-1.6338	2.8461	-0.2693	–	–
β_1	MCMC Mean	-1.5796	2.8450	-0.2690	–	–
β_1	MCMC error	0.2595	0.0416	0.0522	–	–
β_2	True	7.3505	0.4319	1.1724	–	–
β_2	MCMC Mean	7.1099	0.4178	1.1766	–	–
β_2	MCMC error	1.2298	0.0442	0.0334	–	–
β_3	True	-2.9529	-6.4458	9.7919	–	–
β_3	MCMC Mean	-2.8634	-6.4548	9.7907	–	–
β_3	MCMC error	0.4717	0.0461	0.0565	–	–
β_4	True	-2.2035	-9.4002	4.0393	–	–
β_4	MCMC Mean	-2.1458	-9.4045	4.0415	–	–
β_4	MCMC error	0.3626	0.0300	0.0357	–	–
β_5	True	-2.3907	5.4716	6.6912	–	–
β_5	MCMC Mean	-2.3058	5.4648	6.6988	–	–
β_5	MCMC error	0.4575	0.0368	0.0470	–	–

Table A.5: Summary of Monte Carlo error across replications of each parameter set

			MC error			
Parameter Set	N. Clusters	N. Covariates	Mean	Std. Dev.	Minimum	Maximum
1	7	4	0.1968	0.3862	0.0384	1.6139
2	5	3	0.1286	0.2148	0.0379	0.8725
3	4	3	0.1578	0.2158	0.0389	0.7418
4	10	3	0.1747	0.1958	0.0449	0.8134
5	7	5	0.1089	0.2361	0.0376	1.4820
6	1	0	0.1673	0.1673	0.1673	0.1673
7	4	2	0.3718	0.4727	0.0372	1.5248
8	2	5	0.3882	0.4810	0.0325	1.3367
9	10	2	0.3842	0.2792	0.0534	0.9490
10	3	2	0.2480	0.2413	0.0490	0.8220

Table A.7: Summary of the performance of the hdpGLM when estimating number of clusters (K) and linear coefficients (β) across 1000 replications generated by 2 different parameter sets.

	Number of Clusters (K)							
		Estimates across replications				Coverage and HPD of linear coefficients (β)		
Number of Covariates	True	Mean	Minimum	Maximum	Correct (%)	Minimum.	Average	95% HPD (largest average)
4	3	3.03	3	4	96.7	88.21	94.22	(6.8238, 7.3827)
1	5	5.35	5	9	70.2	92.62	97.97	(-1.4744, 4.0107)

Table A.8: Summary of MC error across replications of each parameter set

			MC error			
Parameter Set	N. Clusters	N. Covariates	Mean	Std. Dev.	Minimum	Maximum
1	5	1	0.5387	0.2339	0.2578	0.9238
2	3	4	0.2136	0.3248	0.0300	1.2298

A.5 Example with binary outcome

This section displays a simulation using binary outcome. As the main paper discusses, for binary outcome variable the algorithm uses RMHMC update within Gibbs for the parameter $\boldsymbol{\beta}$. So the MCMC algorithm can take a long time before satisfactory convergence diagnostics are achieved. Therefore, we present results for three simulated cases only, one with no heterogeneity, one with two clusters, and one with three clusters. The procedures adopted are similar to those described in the main paper. We used 80000 burn-in iterations, and 30000 samples were recorded after that. The figures A.2 to A.4 show the estimation for the three cases.

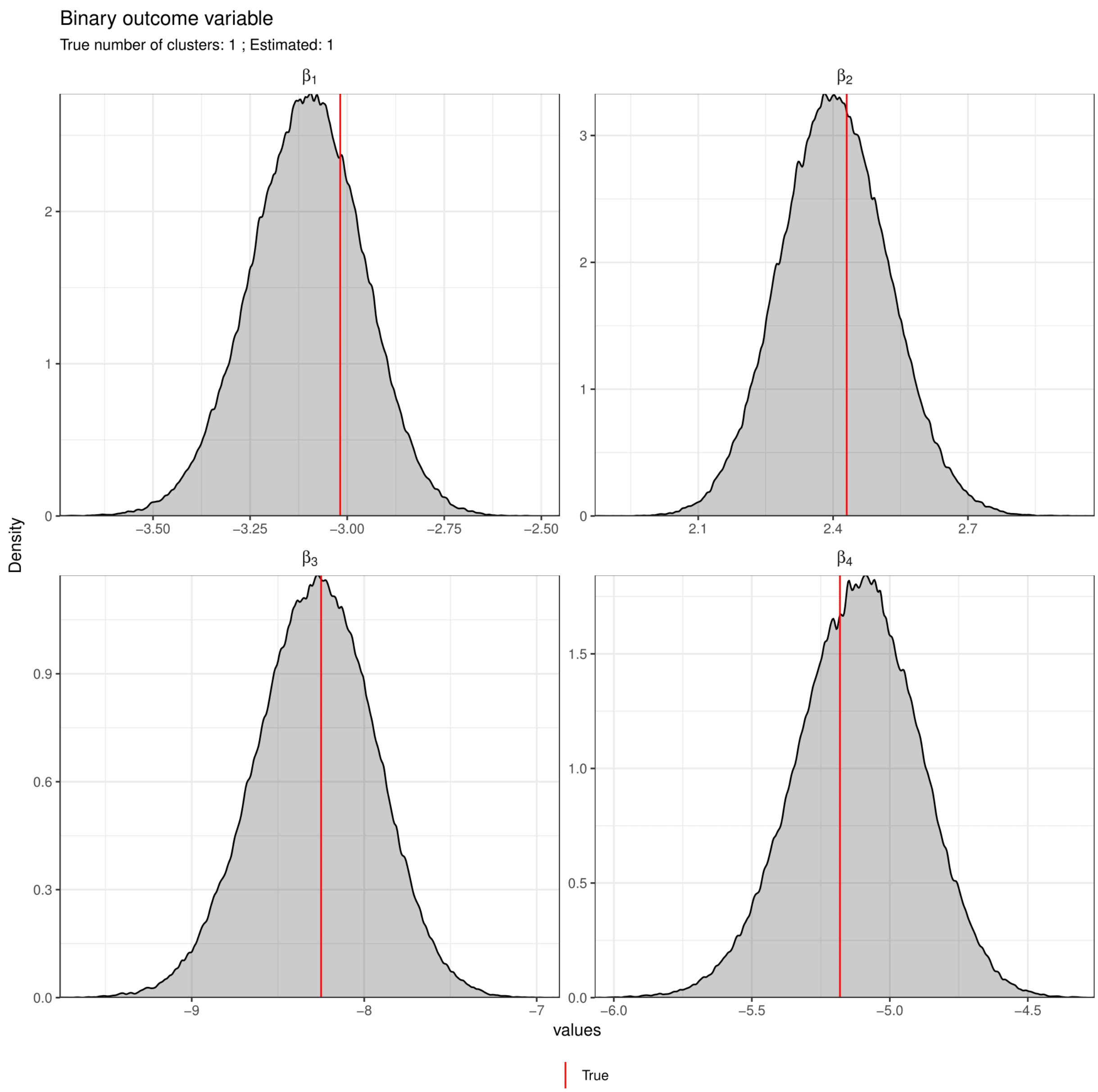


Figure A.2: Estimation of the hdpGLM model with binary outcome variable and one cluster ($K = 1$)

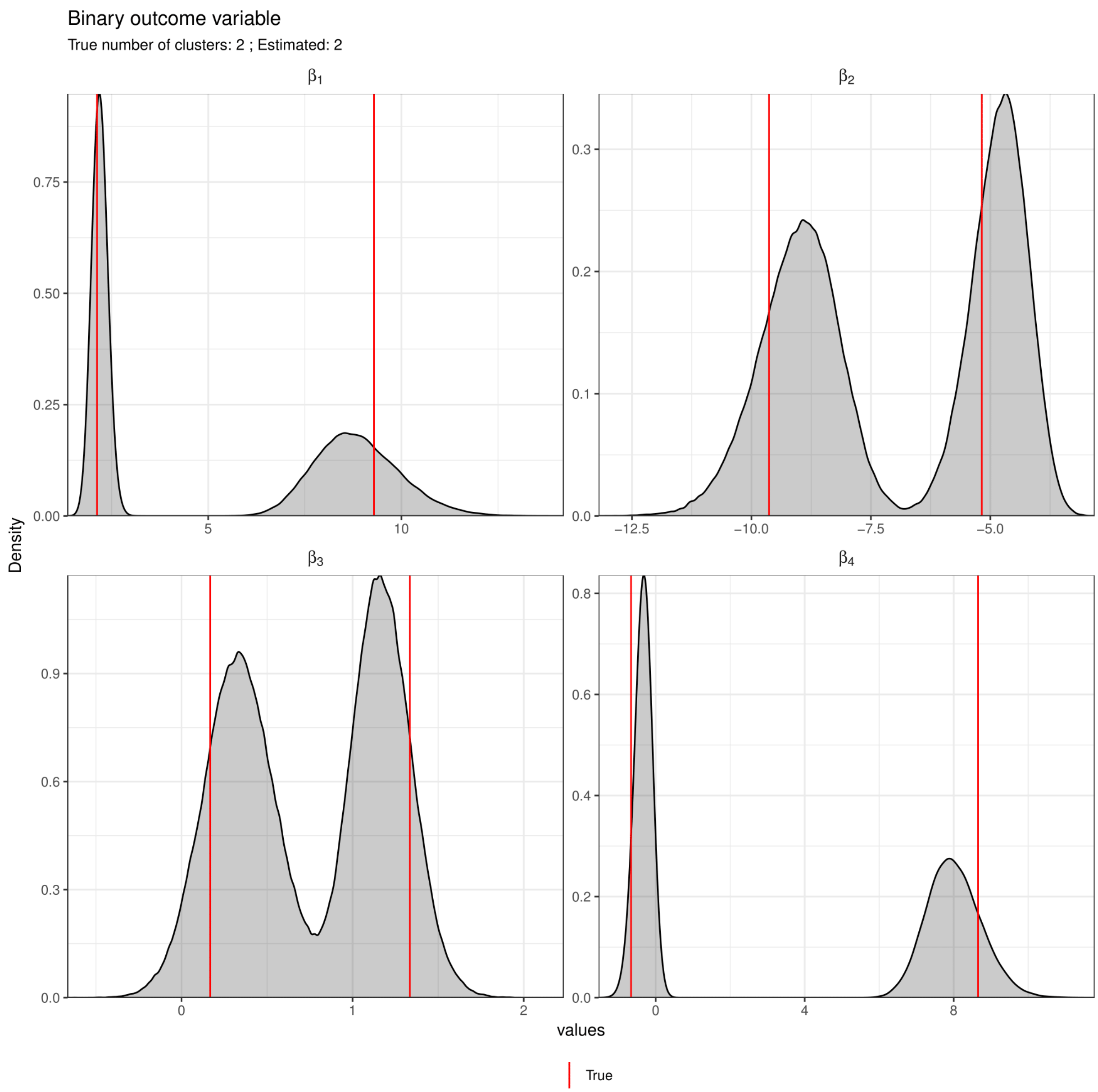


Figure A.3: Estimation of the hdpGLM model with binary outcome variable and two clusters ($K = 2$)

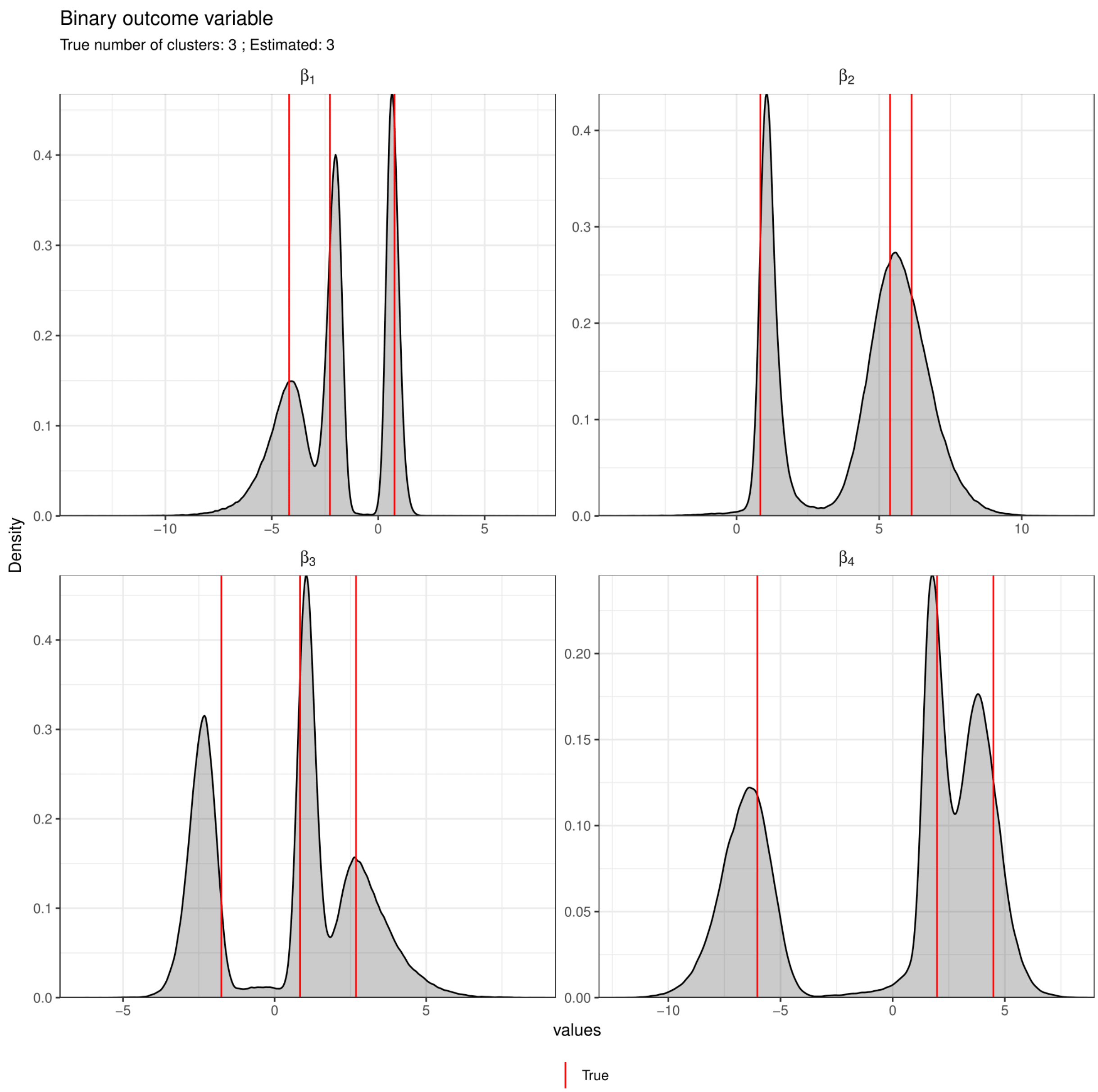


Figure A.4: Estimation of the hdpGLM model with binary outcome variable and three clusters ($K = 3$)

A.6 Marginal Densities of $\boldsymbol{\beta}$

As described in the main paper, we randomly generated 10 parameter sets and, for each one, we generated data sets. The hdpGLM was estimated for each one of the data sets. The Figures A.5 to A.13 display the marginal posterior density plots for the linear coefficients $\boldsymbol{\beta}$ for each data set generated by the parameter sets. The HPDI and the MCMC average in the figures were computed across data sets. As we can see, the posterior densities are located around the true, and the MCMC posterior average is quite close to the true value that generated the data. The estimated number of clusters and the coverage probability of the linear parameters are presented in the main paper.

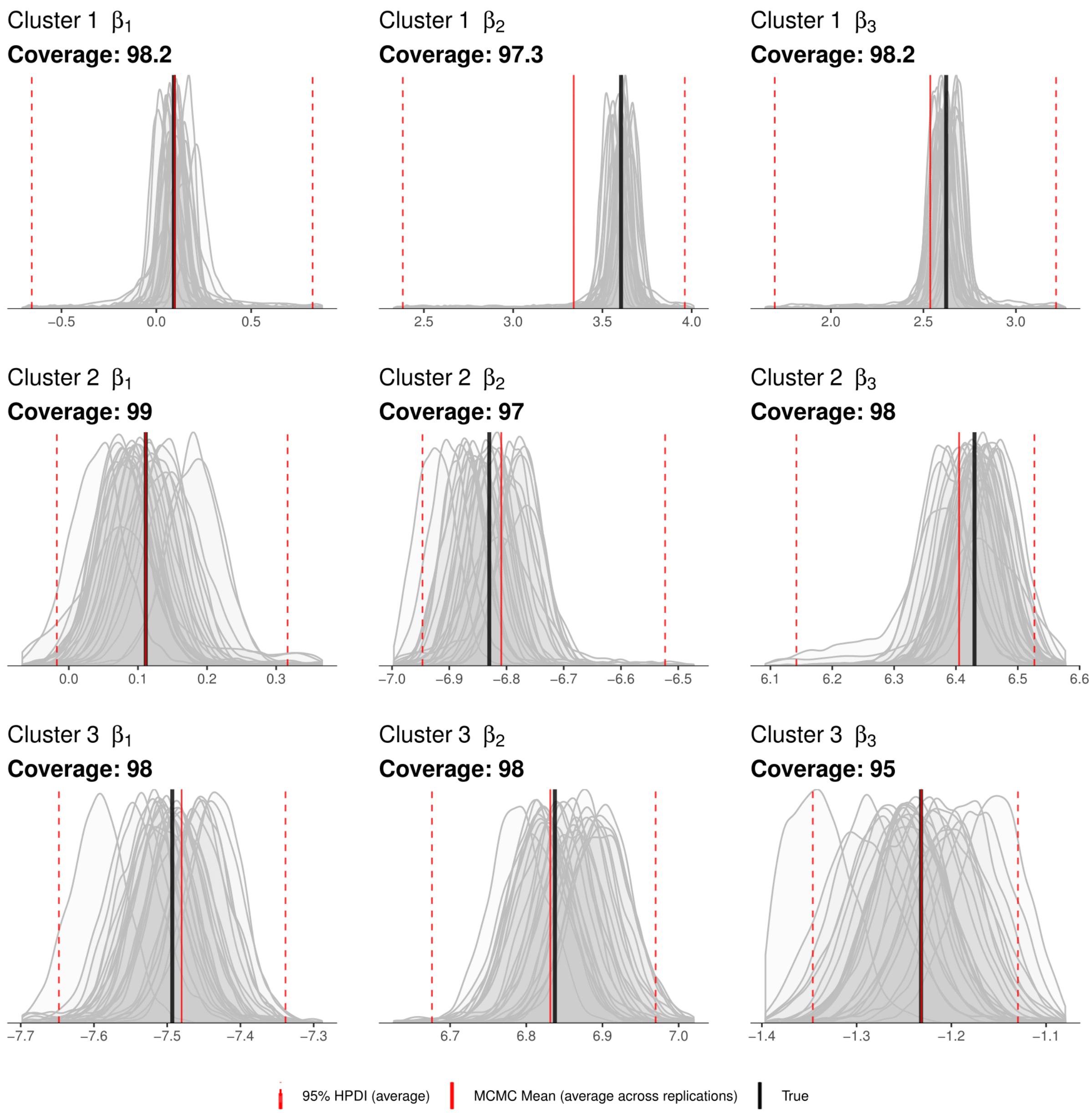


Figure A.5: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 3 clusters and 2 covariates.

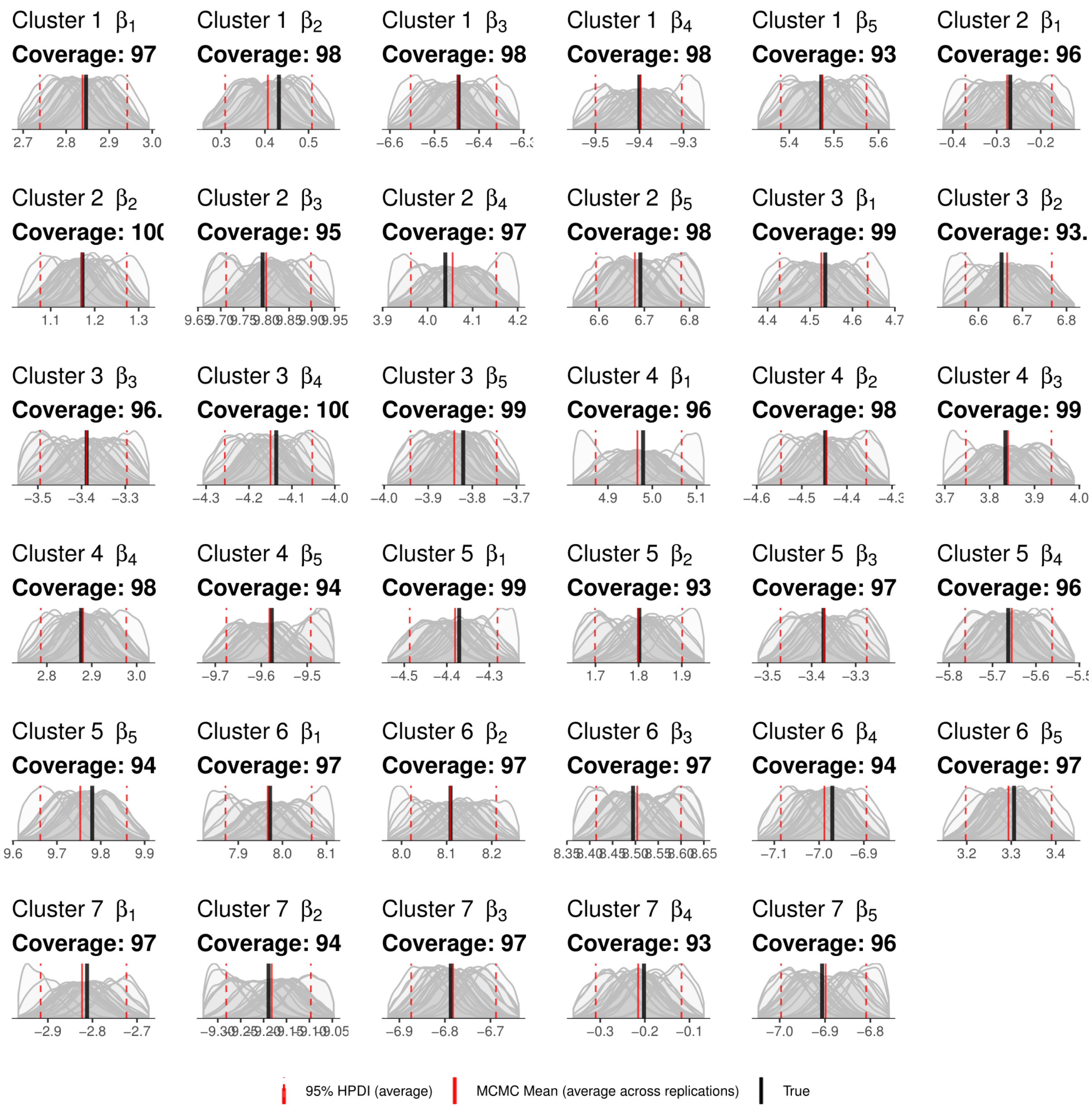


Figure A.6: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 7 clusters and 4 covariates.

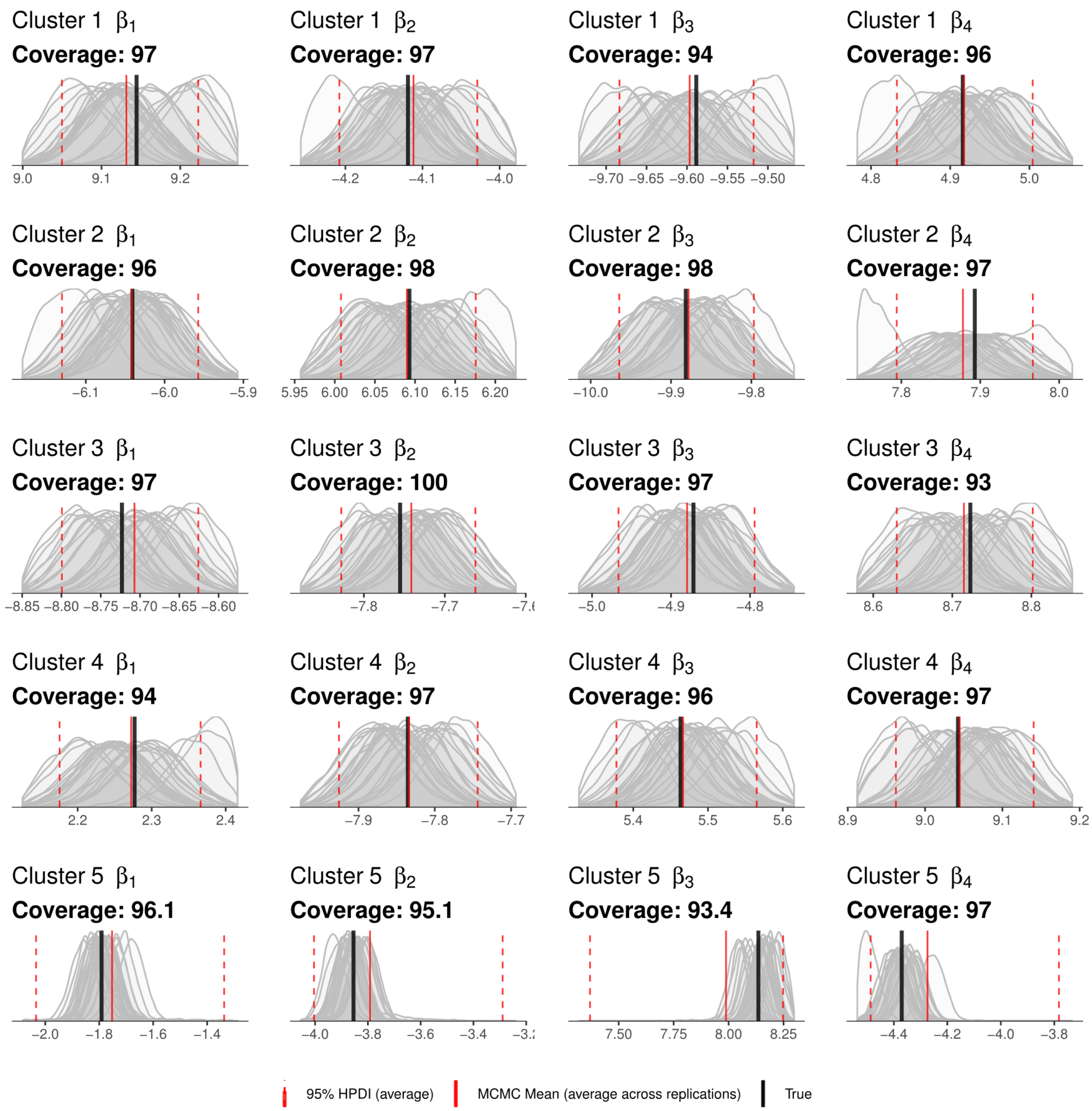


Figure A.7: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 5 clusters and 3 covariates.

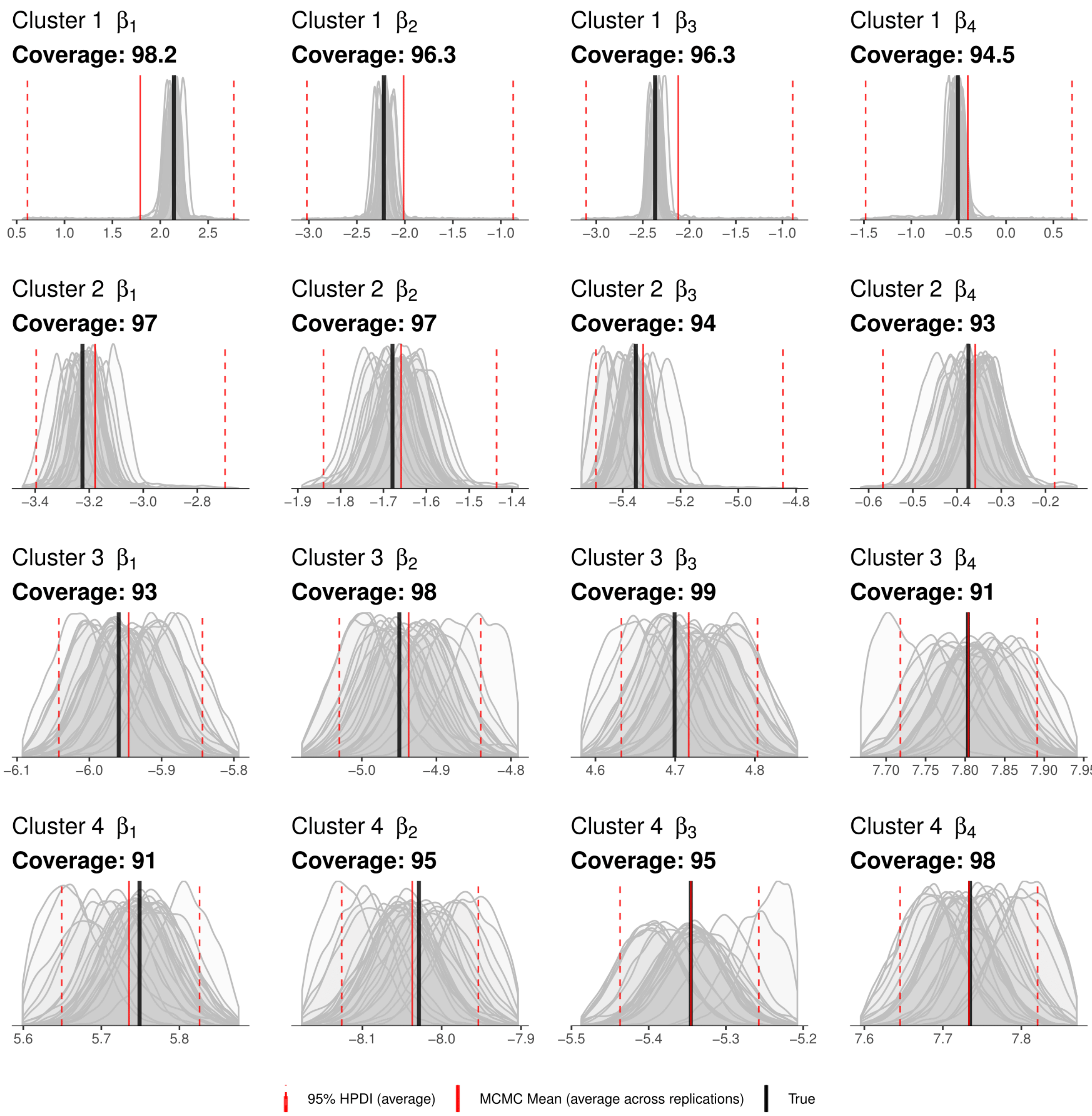


Figure A.8: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 4 clusters and 3 covariates.

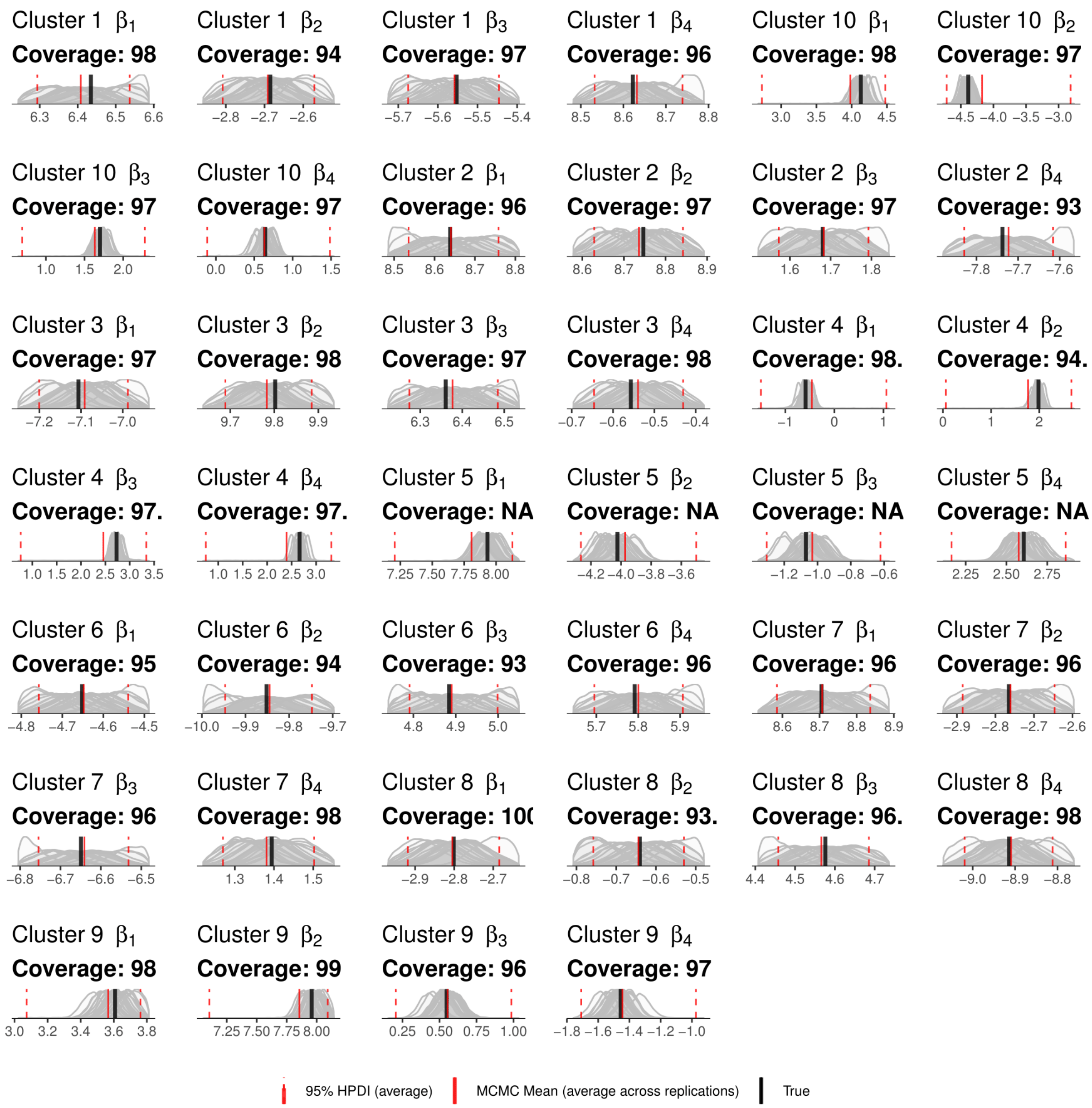


Figure A.9: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 10 clusters and 3 covariates.

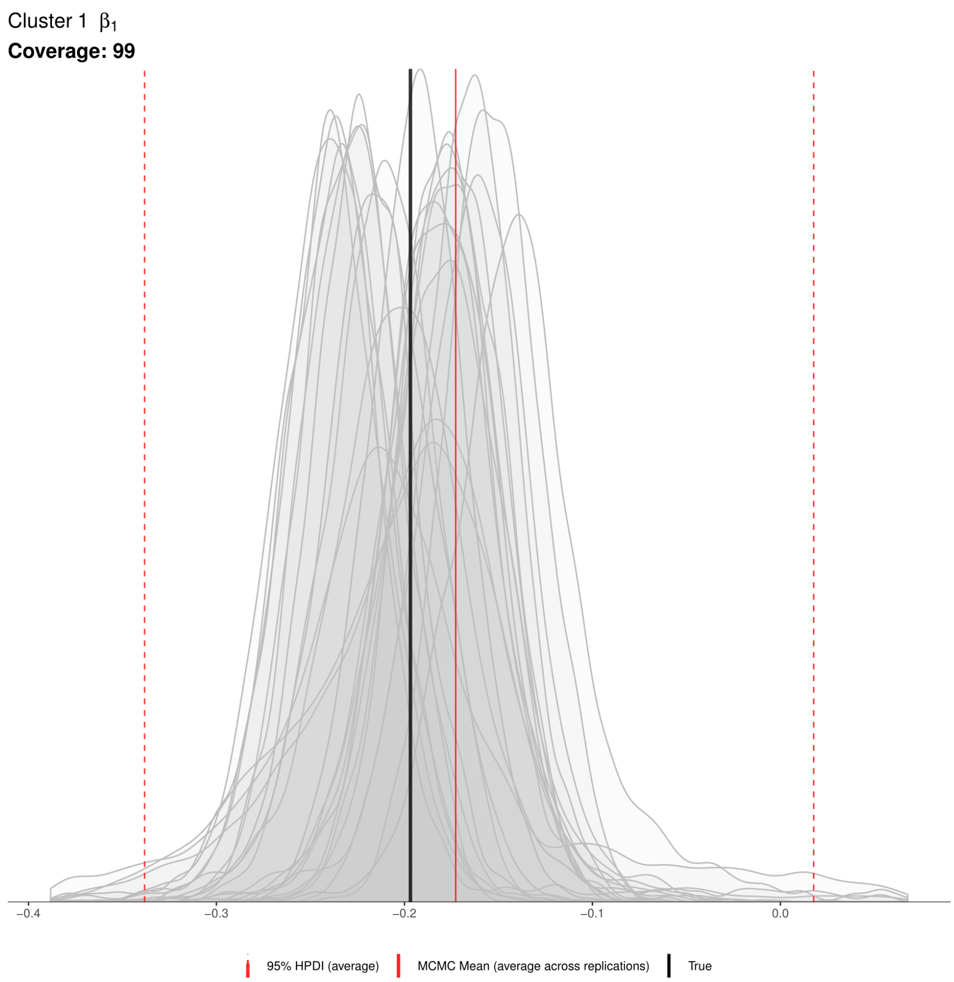


Figure A.10: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 1 cluster and 0 covariates.

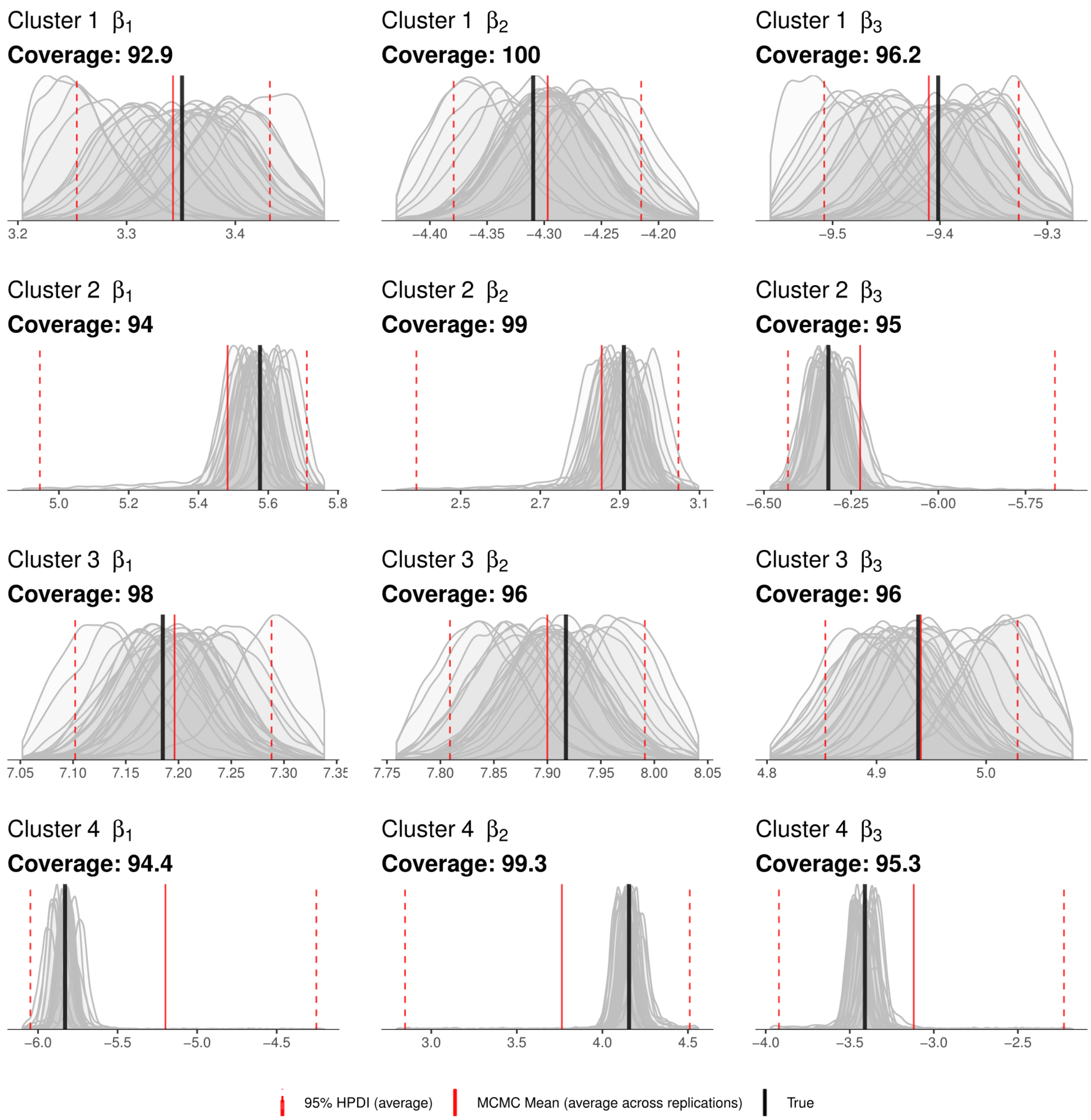


Figure A.11: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 4 clusters and 2 covariates.

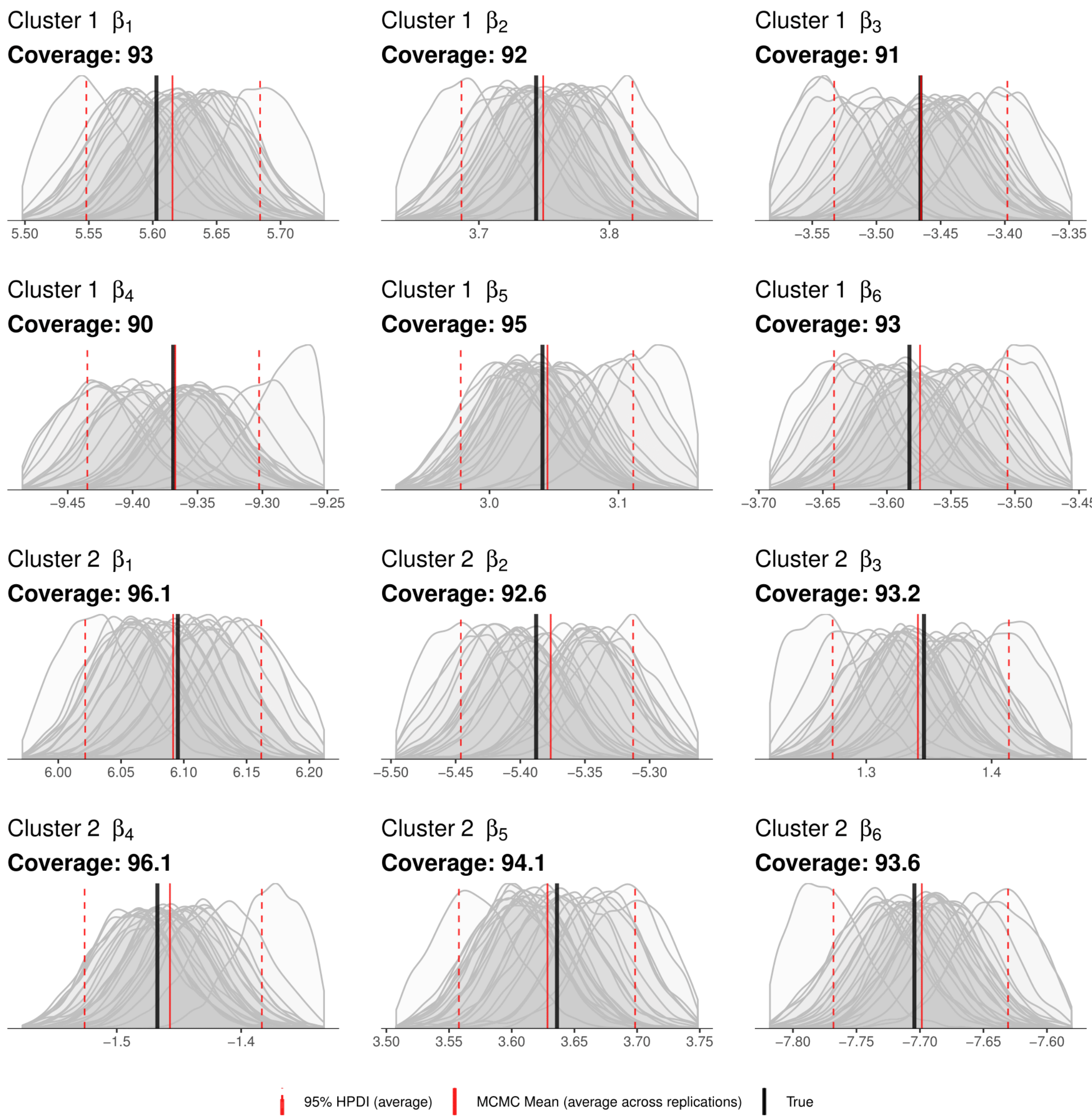


Figure A.12: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 2 clusters and 5 covariates.

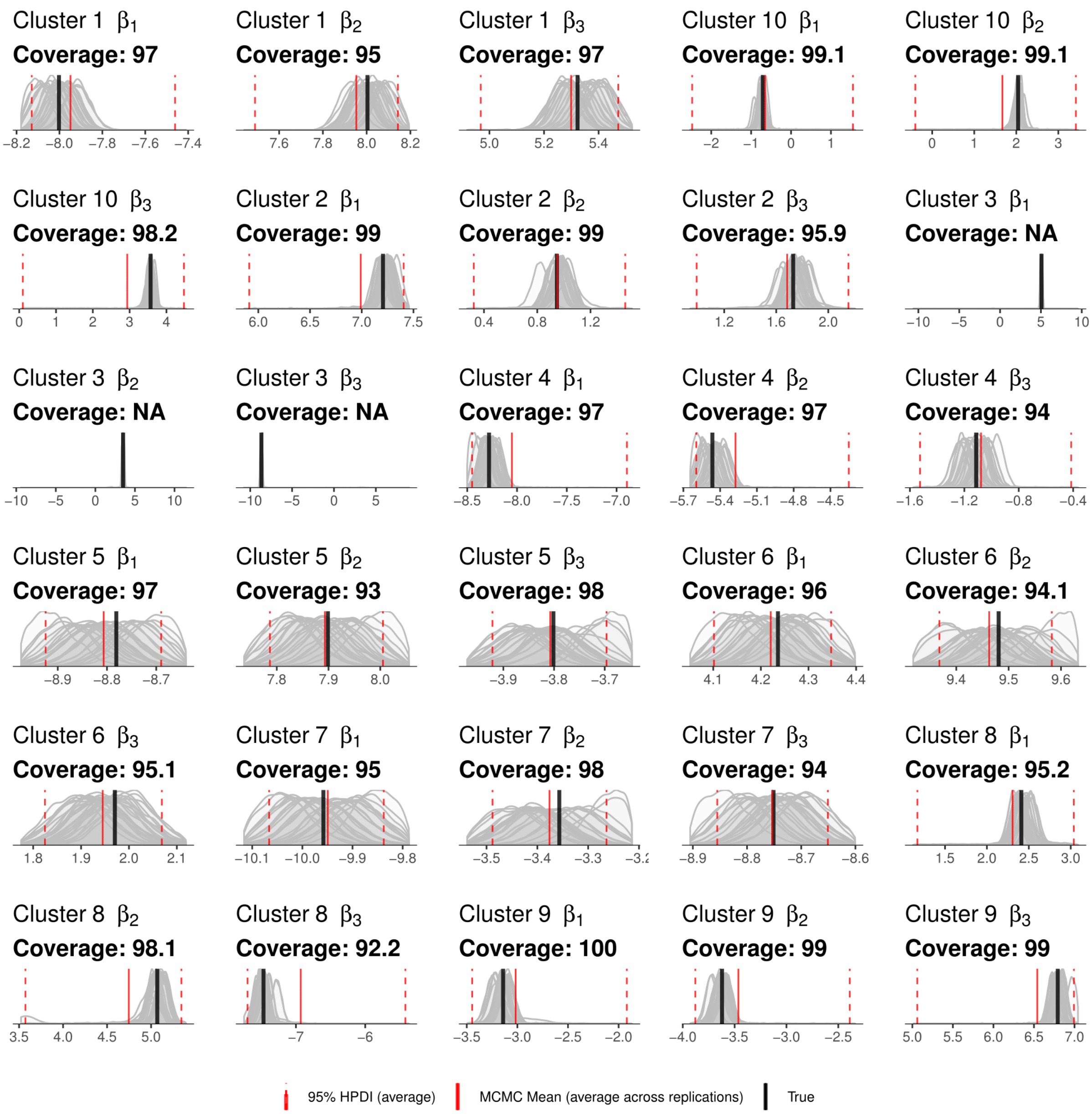


Figure A.13: Marginal Posterior Distribution of β for the estimation of the 50 data sets generated using the parameter set with 10 clusters and 2 covariates.

APPENDIX B

Latent Polarization

B.1 Measure and Estimation of Polarization

To estimate polarization $P(f)$, we follow the procedure developed in Duclos, Esteban and Ray (2004). Let $\hat{y}$ denote the ordered predicted value of the outcome variable $\hat{y}_i = X_i^T \hat{\beta}$. For a chosen level of $\alpha \in [0.25, 1]$, the estimator $\hat{P}(\hat{f})$ of $P(f)$ is:

$$\hat{P}^m(\hat{f}) = \frac{1}{n} \sum_{i=1}^{n} \hat{f}(\hat{y}_i)^{\alpha} \hat{a}(\hat{y}_i) \tag{B.1}$$

where

$$\hat{a}(\hat{y}_i) = \hat{\mu} + \hat{y}_i \left(\frac{1}{n}(2i-1) - 1 \right) - \frac{1}{n} \left(2 \sum_{j=1}^{i-1} \hat{y}_j + \hat{y}_i \right)$$
$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} \hat{y}_i$$

We estimate $f(y)$ using a gaussian kernel $K(z) = (1/h)K(z/h)$ and a bandwidth h (Sheather and Jones, 1991). The estmator is f is:

$$\hat{f}(y_i) = \frac{1}{n} \sum_{j=1}^{n} \hat{K}_h(y_i - y_j)$$

We have that (see Duclos, Esteban and Ray (2004))

$$\frac{1}{n}(\hat{P}(\hat{f}) - P(f)) \sim N(0, V_{\alpha})$$

where

$$V_\alpha = \mathbb{V}\mathrm{ar}_{f(y)}\left[(1-\alpha)f(y)^\alpha a(y) + y\int f(x)dF(x) + 2\int_y^\infty (x-y)f(x)^\alpha dF(x)\right]$$

We can use the plug-in estimator for V_α:

$$\hat{V}_\alpha = \hat{\mathbb{E}}_{\hat{f}(y)}\left[W(\hat{f}) - \mathbb{E}[W(\hat{f})]\right] = \frac{1}{n}\sum_{i=1}^{n}\left(W(\hat{f}) - \mathbb{E}[W(\hat{f})]\right)^2$$

where

$$W(\hat{f}) = (1-\alpha)\hat{f}(y)^\alpha \hat{a}(y) + \frac{y}{n}\sum_{i=1}^{n}\hat{f}(y_i) + \frac{2}{n}\sum_{i=1}^{n}(y_i - y)f(y_i)^\alpha \qquad \text{and}$$

$$\mathbb{E}[W(\hat{f})] = \frac{1}{n}\sum_{i=1}^{n}W_i(\hat{f})$$

APPENDIX C

Socioeconomic Positions, Perceptions, and Support for Redistribution

C.1 Descriptive statistics

C.1.1 Descriptive statistics of all ESS variables

The Table C.1 shows the descriptive statistics of the ESS variables used in the main paper.

Table C.1: Descriptive statistics of the main raw variables.

Variable	N	NAs	Mean	Std.dev	Min	Max
Socio-economic variables						
Income (deciles)	36445	7942	5.1892	2.7336	1.0000	10.0000
Education (years)	43963	424	13.0353	3.8484	0.0000	54.0000
ISEI	40127	4260	43.5530	21.5258	11.0100	88.9600
Age	44232	155	49.1426	18.6133	15.0000	100.0000
Union membership (dummy)	44165	222	0.3874	0.4872	0.0000	1.0000
Unemployed (dummy)	40875	3512	0.0432	0.2033	0.0000	1.0000
Occupation Unemployment Risk	29678	14709	5.8372	4.5293	0.7711	30.5071
Religion (dummy)	44086	301	0.5969	0.4905	0.0000	1.0000
Attitudes on welfare policies (Government should...)						
Ensure basic income for all	40592	3795	0.0565	1.2788	-2.0000	2.0000
Social benefits only for poor while middle and high income are take care of themselves	41825	2562	-0.1619	1.2747	-2.0000	2.0000
Ensure standard of living for the old	44125	262	8.1702	1.8247	0.0000	10.0000
Ensure living standard for unemployed	43838	549	6.7346	2.2722	0.0000	10.0000
Reduce income differences	43715	672	0.8651	0.9984	-2.0000	2.0000
Spend more in training program for unemployed and less in unemployment benefits	41169	3218	0.3832	1.1727	-2.0000	2.0000
Values and Perceptions						
Important to make autonomous decisions and be free	43591	796	4.8176	1.0991	1.0000	6.0000
Important to be modest	43529	858	4.3539	1.2233	1.0000	6.0000
Important to be successful	43459	928	3.8141	1.3741	1.0000	6.0000
A society to be fair, inequality needs to be low	43591	796	0.6073	0.9516	-2.0000	2.0000
Important strong government to ensure safety	43385	1002	4.6581	1.1977	1.0000	6.0000
Important to be rich	43491	896	3.7727	1.4007	1.0000	6.0000
Important to have equal opportunities and be treated equally	43567	820	4.8175	1.0813	1.0000	6.0000
Large inequality is acceptable to reward effort	43520	867	0.0176	1.1329	-2.0000	2.0000
Important to live in safe surroundings	43641	746	4.6325	1.2275	1.0000	6.0000
Confident that can participate in politics	43389	998	-0.8802	1.0486	-2.0000	2.0000
Can take active role in political issues	43452	935	-0.9282	1.0486	-2.0000	2.0000
Social benefits hurt business	41063	3324	-0.0639	1.0506	-2.0000	2.0000
Social benefit hurt country economy	42224	2163	-0.0346	1.0550	-2.0000	2.0000
Social benefits make people lazy	43356	1031	0.0851	1.1232	-2.0000	2.0000
Social benefits lead to equal society	42894	1493	0.2639	1.0101	-2.0000	2.0000
Social benefits make people less solidary	42841	1546	-0.0311	1.0753	-2.0000	2.0000
Too much benefits for many undeserving	41485	2902	0.5181	0.9923	-2.0000	2.0000
Social benefits prevent widespread poverty	43047	1340	0.4155	0.9967	-2.0000	2.0000
Too few benefit to poor that are entitled	39740	4647	0.3317	0.9548	-2.0000	2.0000
Country economy is doing well	43501	886	5.0367	2.3082	0.0000	10.0000
State of the education	40449	3938	5.7986	1.9878	1.0000	9.0000
Government overall performance	41892	2495	5.3113	2.6347	0.0000	10.0000
People like you have a say on what government does	43429	958	-0.7953	0.9432	-2.0000	2.0000
State of the health services	40857	3530	5.6902	2.1455	1.0000	9.0000
People like you can influence politics	43545	842	-0.8578	0.9355	-2.0000	2.0000
Likely to be unemployed soon	34100	10287	-0.9676	1.3108	-2.0000	2.0000
Perceived percentage of unemployed	41329	3058	0.0000	1.0000	-1.3618	2.0354
Most unemployed people do not try to find a job	43313	1074	0.0158	1.0934	-2.0000	2.0000
Unemployed standard of living is not bad	43116	1271	4.0143	2.1419	0.0000	10.0000

C.1.2 PCA construction of the socioeconomic position (SEP) indexes

In this section, we evaluate the construction of the SEP indexes. We compare the PCA results with a factor analysis (PA) and test if one single component can describe well the underlying variables. In the main paper, we used the first PCA component as a measure of SEP, which was constructed in four different ways, three of which used PCA. The first PCA SEP index combines income and education, the second combines income, education and ISEI-08i, the third income, education, ISEI-08, and age. The Figures C.1 to C.3 show the scree plot with the percentage of the variance of the original variables explained by each PCA component. It also shows the vector rotation, and scatter plots with the values of the scores plotted against the original variable values.

The first component of the SEP index created using income and education captures 65.5% of the variance of those two original variables. We inverted the index, so high values of the first component indicate highly educated wealth individuals, as we see in the Figure C.1.

The second SEP index is discribed in the Figure C.2. It includes ISEI-08. The first component captures 62.5% of the variance of the original variables. We also inverted this index, so high values of the component indicate highly educated wealth individuals in high status occupation.

Finally, the last SEP index uses also age to create the PCA score. The first component captures 48.1% of the variance of the original variables. As shown in the Figure C.3, most of the variance of the first component can be attributed to ISEI, income, and education. After inverting the scores, high values of the first component means young, highly educated wealth individuals in high status occupation.

There are various methods to select the number of components (or factors), which include the scree test (Cattell, 1966), the very simple structure criterion (Revelle and Rocklin, 1979), the Wayne Velicer's Minimum Average Partial (MAP) criterion (Velicer, 1976), extracting as many factors as to make the eigenvalue computed using the real data smaller than the corresponding eigenvalue of a random data set of the same size (Horn, 1965), and extracting the components up to engenvalues smaller than one. Each method has its advantages and disadvantages (Horn and Engstrom, 1979). The Figure C.4 shows the PCA and FA eigenvalues of the real data and random data sets of the same size for Austria. We see that one component is enough for all SEP indexes. The same pattern appears for all the other countries. The Table C.2 shows the eigenvalues for each SEP index and country. The last column of the table shows the correlation between the first component of the PCA and the unique factor created by the factor analysis. There is a strong correlation in all cases, and one component is enough for almost all indexes and countries. Very few exceptions appear only for a few countries and SEP indexes constructed with age figuring among the original variables.

The Figure C.5 shows an example of the association between the PCA and the FA scores using data from Austria. The x-axis contains the single factor produced by a factor analysis, and the y-axis shows the PCA components. We can see that the first dimension of the PCA is highly correlated with the single factor from FA. In sum, these results support our choice of the first component of the PCA as the indicator of SEP. Despite of this result, and we test our argument below using all versions of the SEP index and the raw variables individually to check the robustness of the findings across empirical measurements of the socioeconomic position.

Table C.2: Eigenvalues of factor analysis (FA), and principal component analysis (PCA) for each country and SEP

Country	FA 1	FA 2	FA 3	FA 4	PCA 1	PCA 2	PCA 3	PCA 4	Correlation
SEP (income and education)									
Austria	0.6232	0.0000	–	–	1.3116	0.6884	–	–	-1.00
Belgium	0.8041	0.0000	–	–	1.4020	0.5980	–	–	-1.00
Czechia	0.5863	0.0000	–	–	1.2931	0.7069	–	–	1.00
Estonia	0.6203	0.0000	–	–	1.3102	0.6898	–	–	-1.00
Finland	0.7654	0.0000	–	–	1.3827	0.6173	–	–	1.00
France	0.7909	0.0000	–	–	1.3954	0.6046	–	–	1.00
Germany	0.6538	0.0000	–	–	1.3269	0.6731	–	–	-1.00
Hungary	0.7977	0.0000	–	–	1.3989	0.6011	–	–	1.00
Iceland	0.6417	0.0000	–	–	1.3208	0.6792	–	–	-1.00
Ireland	0.9785	0.0000	–	–	1.4892	0.5108	–	–	-1.00
Israel	0.7200	0.0000	–	–	1.3600	0.6400	–	–	1.00
Italy	0.7570	0.0000	–	–	1.3785	0.6215	–	–	1.00
Lithuania	0.6242	0.0000	–	–	1.3121	0.6879	–	–	1.00
Netherlands	0.8413	0.0000	–	–	1.4207	0.5793	–	–	-1.00
Norway	0.5596	0.0000	–	–	1.2798	0.7202	–	–	1.00
Poland	0.7986	0.0000	–	–	1.3993	0.6007	–	–	-1.00
Portugal	1.0337	0.0000	–	–	1.5168	0.4832	–	–	1.00
Russia	0.6299	0.0000	–	–	1.3149	0.6851	–	–	-1.00
Slovenia	0.9051	0.0000	–	–	1.4525	0.5475	–	–	-1.00
Spain	0.9880	0.0000	–	–	1.4940	0.5060	–	–	-1.00
Sweden	0.7363	0.0000	–	–	1.3682	0.6318	–	–	1.00
Switzerland	0.7557	0.0000	–	–	1.3779	0.6221	–	–	-1.00
UK	0.8953	0.0000	–	–	1.4476	0.5524	–	–	1.00
SEP (income, education, and ISEI-08)									

Table C.2: Eigenvalues of factor analysis (FA), and principal component analysis (PCA) for each country and SEP *(continued)*

Country	FA 1	FA 2	FA 3	FA 4	PCA 1	PCA 2	PCA 3	PCA 4	Correlation
Austria	1.4625	0.0000	0.0000	–	1.8738	0.7866	0.3397	–	-0.98
Belgium	1.5053	0.0000	0.0000	–	1.9443	0.6922	0.3635	–	-0.98
Czechia	1.3853	0.0000	0.0000	–	1.8211	0.7853	0.3937	–	0.95
Estonia	1.4151	0.0000	0.0000	–	1.8711	0.7472	0.3817	–	-0.98
Finland	1.4948	0.0000	0.0000	–	1.9539	0.6597	0.3863	–	0.98
France	0.9300	0.0000	0.0000	–	1.5566	0.8540	0.5894	–	0.97
Germany	1.5546	0.0000	0.0000	–	1.9541	0.7190	0.3269	–	-0.97
Hungary	1.6808	0.0000	0.0000	–	2.0185	0.7078	0.2737	–	0.95
Iceland	1.4239	0.0000	0.0000	–	1.8673	0.7632	0.3695	–	-0.98
Ireland	1.5661	0.0000	0.0000	–	2.0313	0.5596	0.4091	–	-0.99
Israel	1.3625	0.0000	0.0000	–	1.8482	0.7379	0.4140	–	-0.98
Italy	1.5740	0.0000	0.0000	–	1.9925	0.6666	0.3409	–	0.98
Lithuania	1.5118	0.0000	0.0000	–	1.8732	0.7753	0.3515	–	0.92
Netherlands	1.5576	0.0000	0.0000	–	1.9923	0.6529	0.3548	–	-0.98
Norway	1.4408	0.0000	0.0000	–	1.8561	0.7953	0.3486	–	0.97
Poland	1.7242	0.0000	0.0000	–	2.0531	0.7025	0.2444	–	-0.97
Portugal	1.8734	0.0000	0.0000	–	2.2064	0.5525	0.2412	–	0.98
Russia	1.3292	0.0000	0.0000	–	1.7935	0.7833	0.4232	–	-0.96
Slovenia	1.6449	0.0000	0.0000	–	2.0225	0.6604	0.3171	–	-0.95
Spain	1.6944	0.0000	0.0000	–	2.0994	0.5734	0.3271	–	-0.99
Sweden	1.4073	0.0000	0.0000	–	1.8876	0.7030	0.4093	–	0.98
Switzerland	1.4490	0.0000	0.0000	–	1.9044	0.7122	0.3834	–	-0.98
UK	1.4651	0.0000	0.0000	–	1.9683	0.5720	0.4596	–	0.99
SEP (income, education, ISEI-08, and age)									
Austria	1.5021	0.0812	0.0303	-0.1116	1.9246	0.9677	0.7830	0.3247	-0.96
Belgium	1.5544	0.2099	0.0320	-0.2419	2.0048	1.0434	0.6279	0.3240	-0.95
Czechia	1.4072	0.3363	-0.0682	-0.2681	1.9578	1.0900	0.5610	0.3911	0.96
Estonia	1.4224	0.3952	-0.0746	-0.3206	1.9749	1.1546	0.4891	0.3814	-0.98
Finland	1.5170	0.1441	0.0307	-0.1748	1.9982	0.9956	0.6587	0.3476	0.98
France	1.3145	0.2571	-0.0627	-0.2118	1.6214	1.1716	0.7555	0.4515	-0.83
Germany	1.5573	0.1612	0.0017	-0.1630	1.9541	1.0742	0.6465	0.3252	-0.96
Hungary	1.7488	0.1992	-0.0213	-0.1779	2.1463	0.9585	0.6289	0.2663	0.93
Iceland	1.4226	0.2170	0.0024	-0.2194	1.8761	1.1067	0.6613	0.3559	-0.97
Ireland	1.7127	0.2020	0.0137	-0.2156	2.1763	0.9538	0.5540	0.3159	-0.96
Israel	1.3805	0.1227	0.0245	-0.1472	1.8684	1.0163	0.7234	0.3919	-0.97
Italy	1.6469	0.2525	-0.0513	-0.2012	2.0523	1.0393	0.6437	0.2647	0.94
Lithuania	1.5755	0.3625	-0.0993	-0.2632	2.1068	1.0412	0.5125	0.3395	0.96
Netherlands	1.5763	0.1172	0.0176	-0.1348	2.0260	0.9953	0.6365	0.3422	-0.98
Norway	1.4381	0.1041	0.0094	-0.1135	1.8601	1.0167	0.7890	0.3342	0.98
Poland	1.8067	0.2376	-0.0209	-0.2167	2.2059	0.9630	0.5987	0.2324	-0.95
Portugal	2.0018	0.1742	0.0096	-0.1837	2.3381	0.9261	0.5513	0.1845	0.93
Russia	1.3870	0.3249	-0.0542	-0.2706	1.9500	1.0737	0.5784	0.3979	-0.95
Slovenia	1.7139	0.2975	-0.0007	-0.2968	2.1303	1.0689	0.5211	0.2796	-0.93
Spain	1.7868	0.1308	0.0262	-0.1570	2.2075	0.9312	0.5732	0.2881	-0.96

Table C.2: Eigenvalues of factor analysis (FA), and principal component analysis (PCA) for each country and SEP *(continued)*

Country	FA 1	FA 2	FA 3	FA 4	PCA 1	PCA 2	PCA 3	PCA 4	Correlation
Sweden	1.4758	0.1908	0.0538	-0.2447	1.9381	1.0451	0.6736	0.3432	0.94
Switzerland	1.4530	0.1654	0.0047	-0.1701	1.9133	1.0568	0.6565	0.3733	-0.97
UK	1.5001	0.1484	0.0401	-0.1886	2.0293	0.9893	0.5727	0.4087	0.99

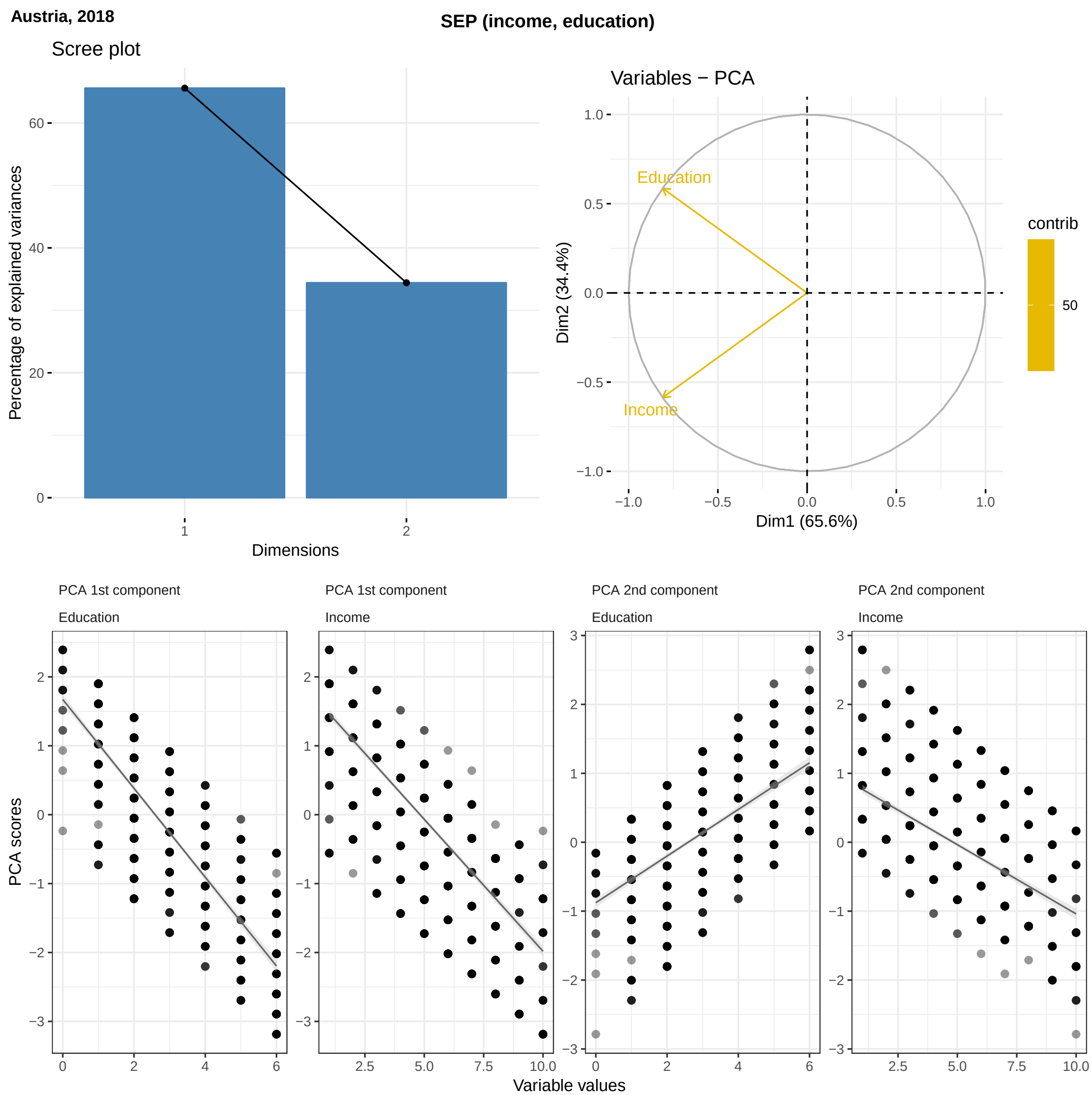


Figure C.1: PCA summary for SEP constructed using income (deciles) and education (7 levels); example with Austria.

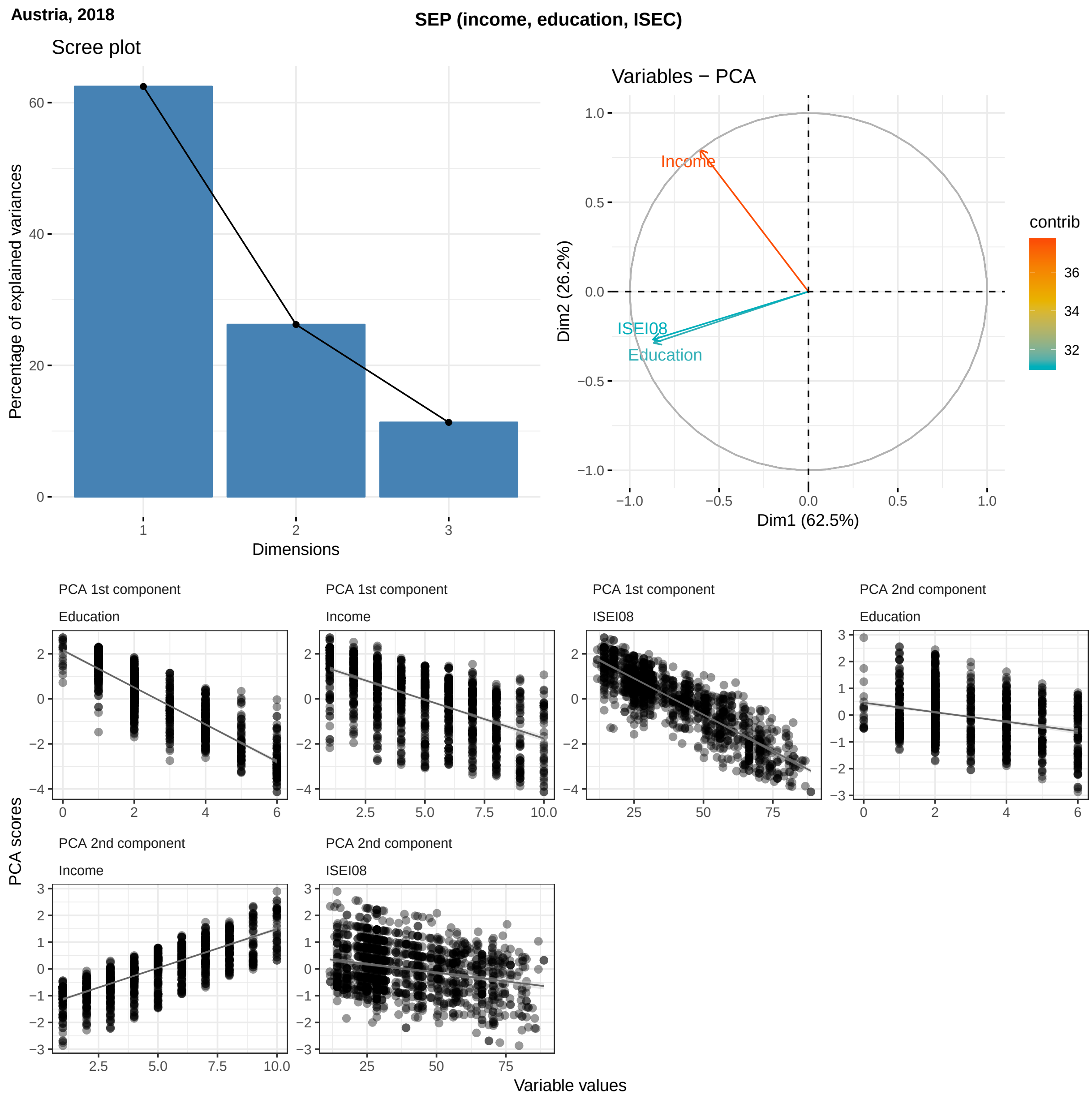


Figure C.2: PCA summary for SEP constructed using income (deciles), education (7 levels), and ISEI08; example with Austria.

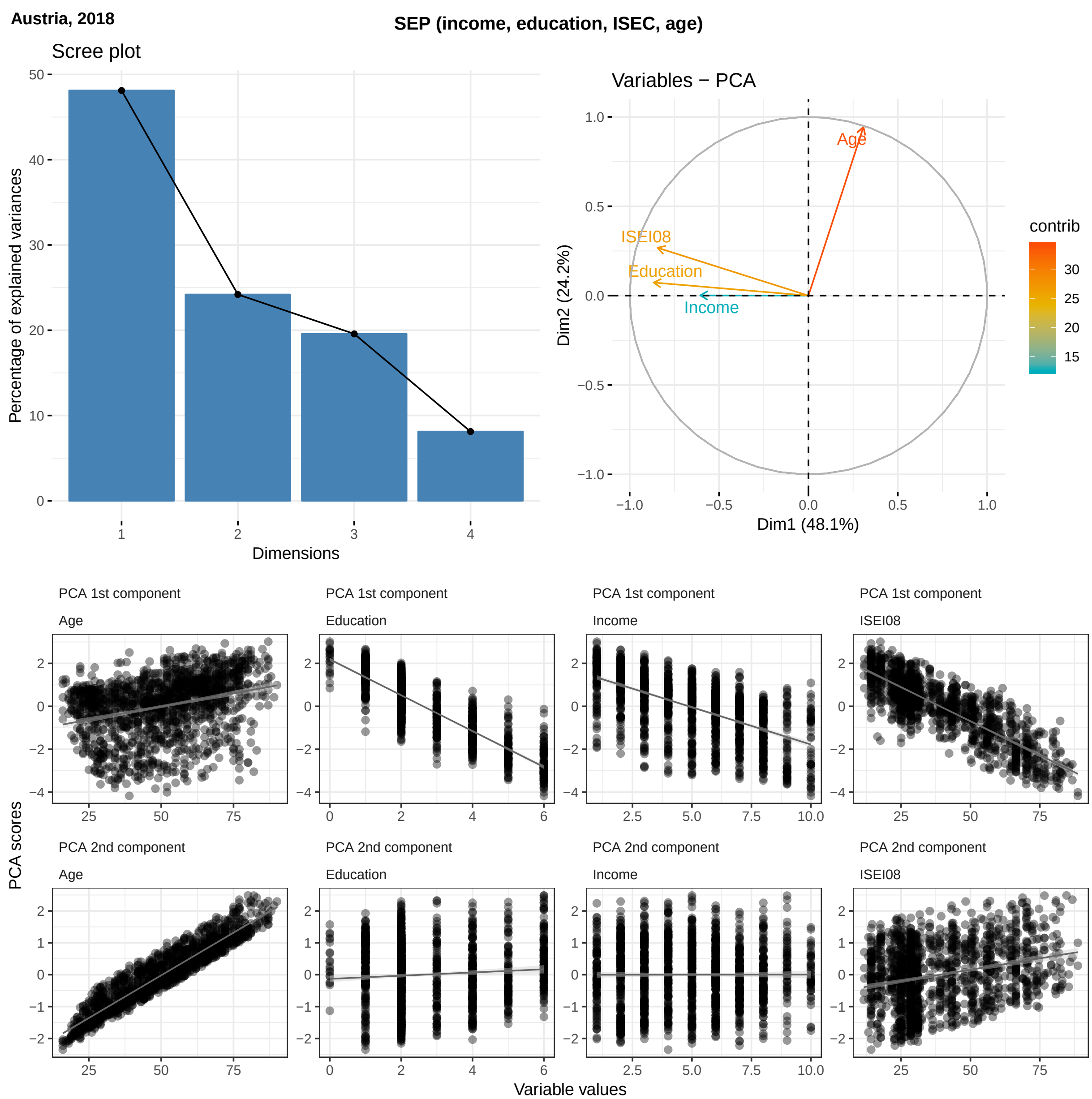


Figure C.3: PCA summary for SEP constructed using income (deciles), education (7 levels), ISEI08, and age; example with Austria.

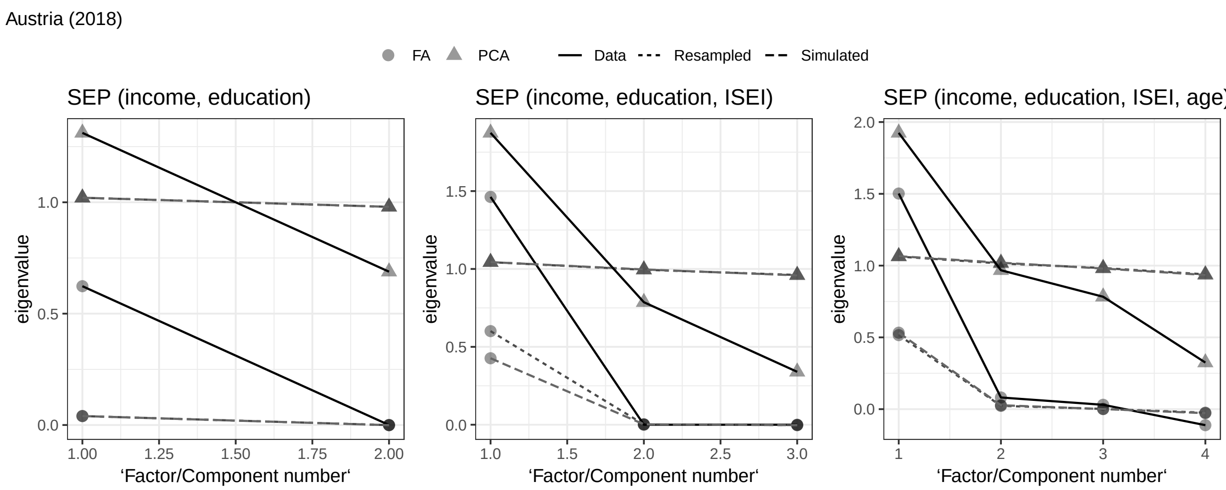


Figure C.4: Comparing eigenvalues from PCA, FA, data, and random sample data; example with Austria.

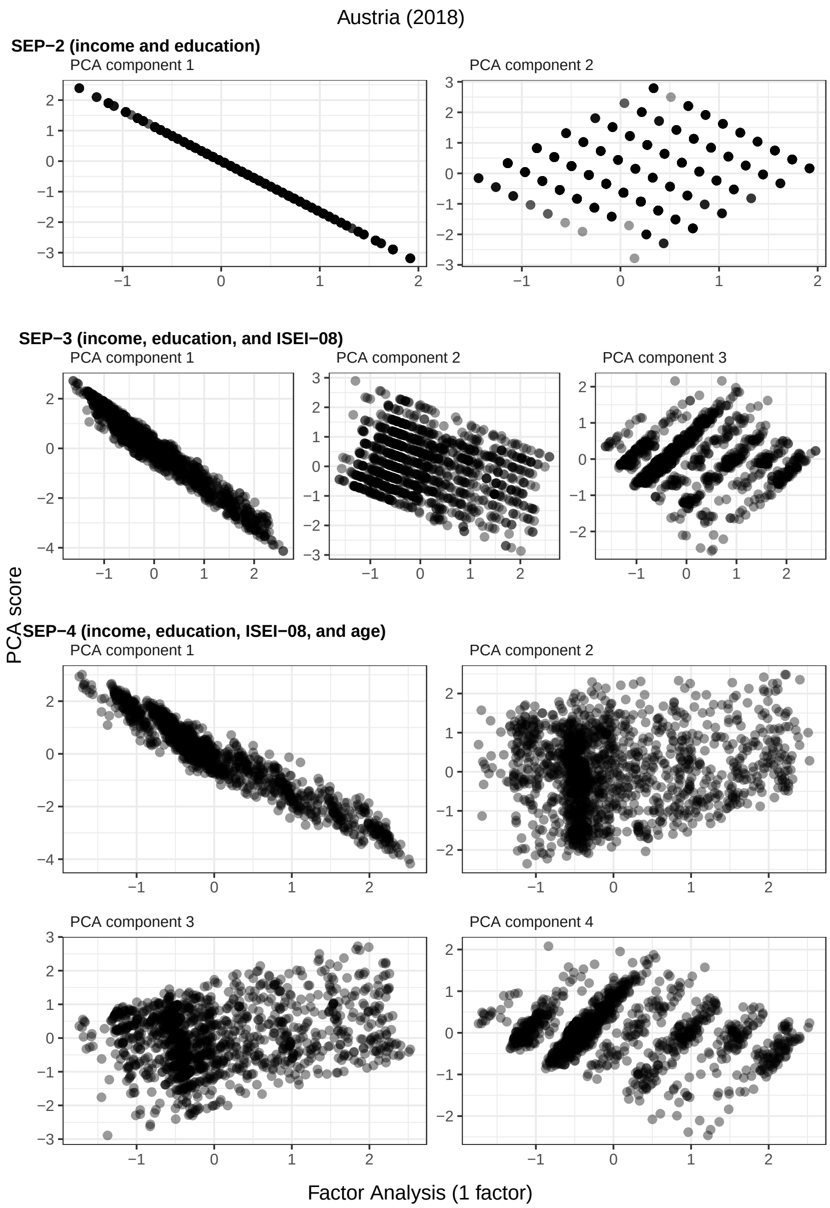


Figure C.5: Comparing PCA and FA scores for SEP for Austria

C.1.3 PCA construction of the unemployment pessimism index

We used a PCA *unemployment pessimism* index in the main paper, which was constructed using three questions:

1. How likely will be unemployed in the next 12 months? (4 points scale)
2. What is the percentage of unemployed in your country? (0-100)
3. What do you think about the standard of living of people who are unemployed? (11 points scale)

The main paper uses the first component of the index. The Figure C.6 shows the summaries of the components. The first component explains 40.1% of the variance of the original variables. We inverted the index, so high values indicate people that perceive enemployment as very high, and think it is very likely they can be unemployed in the next 12 months. They think, additionally, that the standard of living of the unemployed is bad. In this section, we repeat the procedure we did in the section C.1.2, and evaluate if one component is adequate to represent the perceptions about unemployment.

The Figure C.7 shows an example with data from Austria. The Figure shows the eigenvalues of the PCA and FA for the data and a data set randomly generated. We see that one component is sufficient if we rely on the eigenvalue method (Horn, 1965; Horn and Engstrom, 1979; Cattell, 1966; Velicer, 1976). The same patterns appear for the other countries. The Table C.3 displays the eigenvalues for all other countries, as well as the correlation between the first component of the PCA and the single factor from FA. For most of the cases, the PCA eigenvalue is smaller than one in the second component.

Moreover, the results do not change if we use the raw variables instead of the PCA index. The Table C.4 shows that the the SEP index used in the main paper is highly correlated with all four ways to measure perceptions about unemployment, i.e., the PCA component and the three original variables used to create the index. The higher the SEP, the lower the pessimism, the perception about chances of becoming unemployed in the next 12 months, and the perception about the number of unemployed in the country. Moreover, the higher the SEP, the more people think that the standard of living of the unemployed is not bad. These results are all consistent with the argument in the main paper. The Table C.5 shows that the results in the main paper are similar if we used the PCA index or the variables individually.

Table C.3: Comparing PCA and FA analysis for unemployment pessimism index.

Country	FA 1	FA 2	FA 3	PCA 1	PCA 2	PCA 3	Correlation
Austria	0.4146	0.0000	0.0000	1.2037	0.9502	0.8460	-0.9199
Belgium	1.0197	0.0279	-0.0283	1.1517	1.0125	0.8358	0.7679
Switzerland	0.5595	0.0000	0.0000	1.1844	0.9716	0.8440	-0.8386
Czechia	1.0116	0.0608	-0.0616	1.1090	1.0483	0.8428	-0.7812
Germany	1.0038	0.0109	-0.0110	1.0905	1.0064	0.9032	0.7502
Estonia	0.3989	0.0000	0.0000	1.2622	0.8869	0.8508	0.9963
Spain	0.6422	0.0000	0.0000	1.4113	0.8394	0.7493	0.9861
Finland	0.2361	0.0000	0.0000	1.1449	0.9557	0.8994	-0.9860
France	1.0189	0.0155	-0.0157	1.1519	1.0051	0.8430	-0.7640
United Kingdom	1.0116	0.0509	-0.0516	1.1140	1.0370	0.8490	0.7731
Hungary	1.0134	0.0367	-0.0371	1.1268	1.0215	0.8518	-0.7660
Ireland	0.3778	0.0000	0.0000	1.2370	0.9221	0.8408	-0.9893
Israel	1.0450	0.0277	-0.0288	1.2206	1.0058	0.7736	0.7833
Iceland	0.1803	0.0000	0.0000	1.1023	0.9790	0.9187	0.9800
Italy	0.5898	0.0000	0.0000	1.3184	0.9183	0.7633	0.9381
Lithuania	1.0146	0.0492	-0.0500	1.1236	1.0370	0.8394	0.7845
Netherlands	0.4074	0.0000	0.0000	1.2679	0.8853	0.8467	0.9968
Norway	0.4656	0.0000	0.0000	1.2128	0.9526	0.8345	-0.9012
Poland	0.2478	0.0000	0.0000	1.1541	0.9460	0.8999	0.9842
Portugal	0.5417	0.0000	0.0000	1.2903	0.9202	0.7895	0.9339
Russia	0.4714	0.0000	0.0000	1.3037	0.8842	0.8122	0.9919
Sweden	0.3597	0.0000	0.0000	1.1792	0.9612	0.8596	0.9325
Slovenia	0.4158	0.0000	0.0000	1.2436	0.9433	0.8131	0.9812

In sum, the results support our choice of the unemployment pessimisn index to illustrate the effect of perceptions about the unemployment, as well as the argument in the main paper about how those perceptions are affected by the SEP, and how they affect normative preferences about unemployment policies.

Table C.4: Regression of various measures of perception of unemployment on socioeconomic positions (SEP).

	Unemployment pessimism	Likely to be unemployed soon	Perceived percentage of unemployed	Unemployed standard of living is not bad
	(1)	(2)	(3)	(4)
‘SEP (income, education, ISEI-08)‘	−0.165	−0.104	−0.192	0.031
	(−0.176, −0.155)	(−0.118, −0.090)	(−0.202, −0.183)	(0.011, 0.051)
‘Occup. Unemp. Risk (OUR)‘	−0.008	0.016	−0.004	−0.009
	(−0.012, −0.005)	(0.011, 0.022)	(−0.007, 0.0003)	(−0.017, −0.001)
N	29,297	23,172	27,814	28,665
Log Likelihood	−42,127.430	−35,904.380	−35,444.600	−58,701.870
AIC	84,274.860	71,828.750	70,909.210	117,423.700
BIC	84,357.710	71,909.260	70,991.540	117,506.400

Random effects at the country level. Controls (omitted): Age, Occup. Unemp. Risk (OUR), Gender, Unemployment, Unionism, Religion attendance

Table C.5: Regression of policy preference (It’s governments’ responsibility to ensure reasonable standard of living for the unemployed) on SEP and perceptions about unemployment.

	It’s governments’ responsibility to ensure reasonable standard of living for the unemployed			
	(1)	(2)	(3)	(4)
‘SEP (income, education, ISEI-08)‘	−0.030	−0.029	−0.038	−0.053
	(−0.053, −0.007)	(−0.054, −0.003)	(−0.062, −0.014)	(−0.075, −0.030)
‘Unemployment pessimism‘	0.165			
	(0.141, 0.189)			
‘Likely to be unemployed soon‘		0.106		
		(0.082, 0.130)		
‘Perceived percentage of unemployed‘			0.086	
			(0.057, 0.115)	
‘Unemployed standard of living is not bad‘				−0.225
				(−0.238, −0.212)
‘Occup. Unemp. Risk (OUR)‘	0.013	0.011	0.014	0.009
	(0.004, 0.022)	(0.001, 0.022)	(0.005, 0.024)	(−0.00004, 0.018)
N	29,013	22,999	27,629	28,475
Log Likelihood	−62,981.100	−49,796.250	−59,957.530	−61,286.050
AIC	125,984.200	99,614.500	119,937.100	122,594.100
BIC	126,075.200	99,702.980	120,027.600	122,684.900

Random effects at the country level. Controls (omitted): Age, Occup. Unemp. Risk (OUR), Gender, NotEmployment, Unionism, Religion attendance

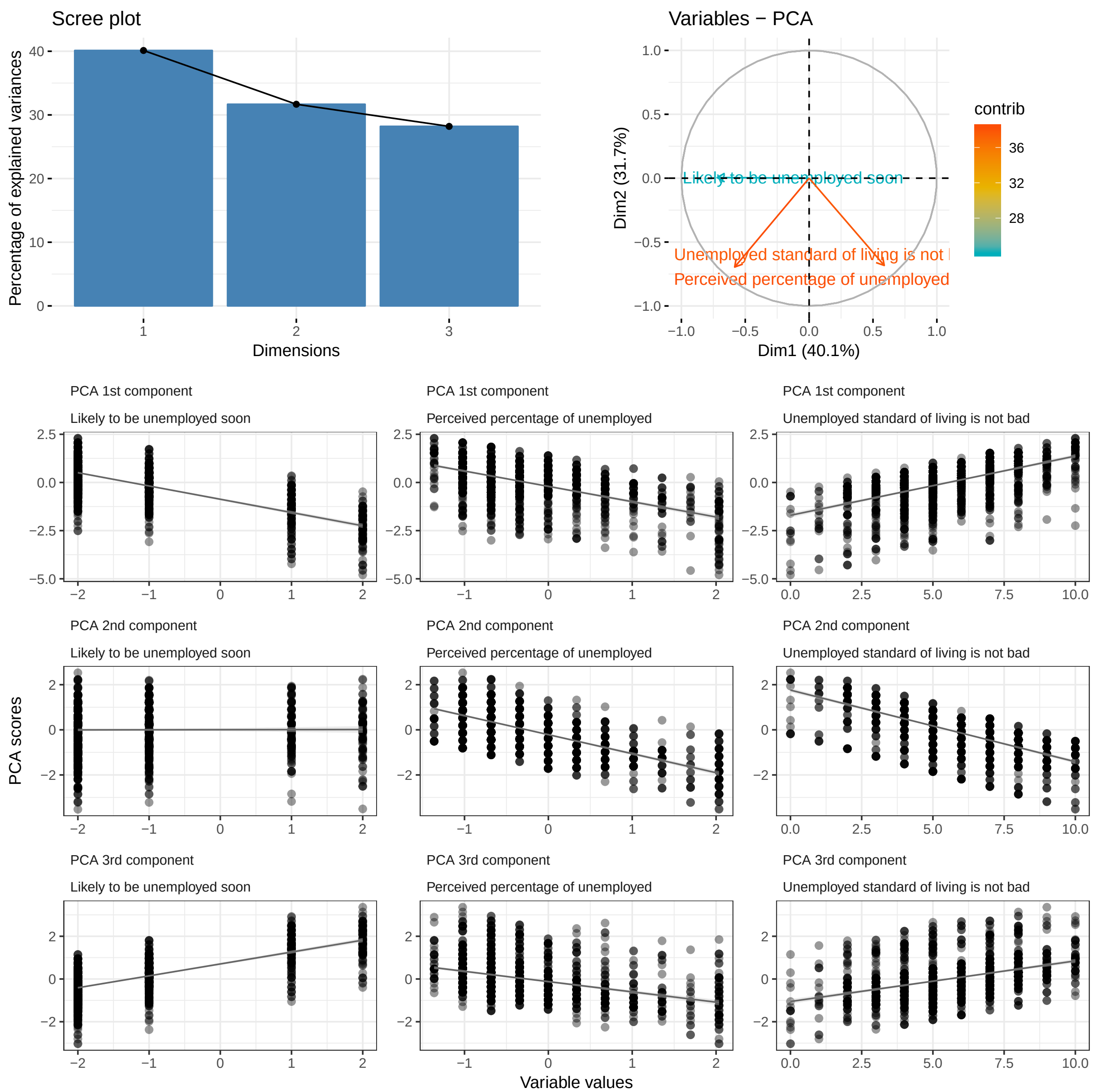


Figure C.6: PCA components to construct the unemployment pessimism index

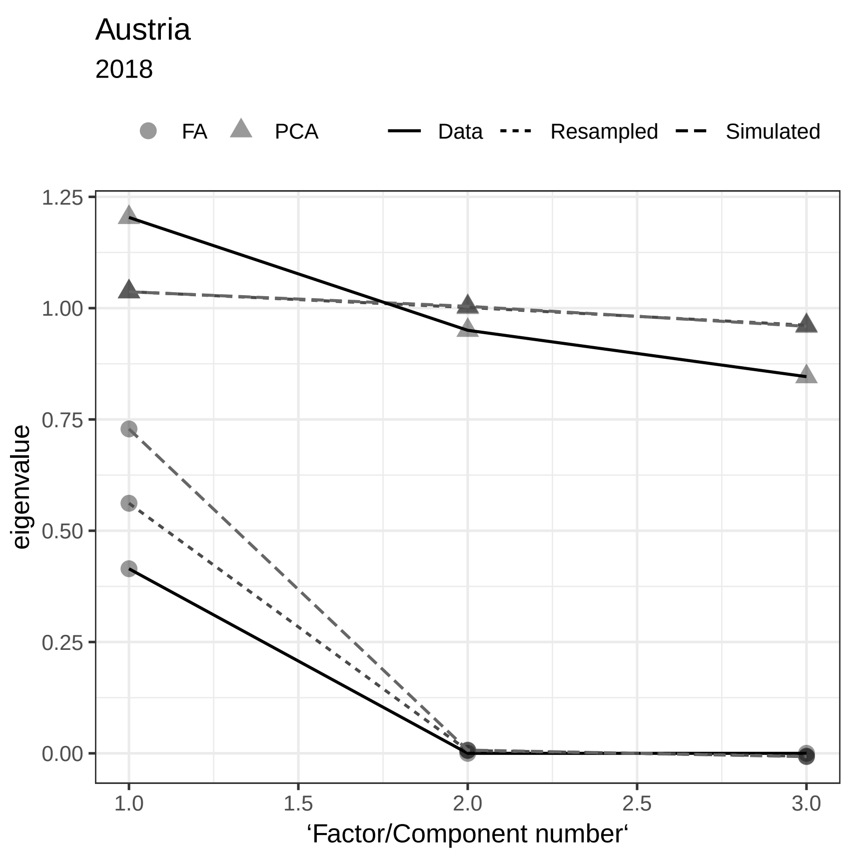


Figure C.7: Eigenvalues of PCA and FA to construct unemployment pessimism index; example with Austria

C.1.4 Barplots: Socioeconomic positions, perceptions, and welfare policy attitudes

The main paper contains a descriptive barplot showing the average value of the policy preference for each income group (Poor, Middle class, and Rich) and the answers about the question that measure perceptions about different aspects of the socioeconomic environment. This section shows the same plots, but for all policies and perception dimensions used in the paper. The Figure C.8 shows the summary for the policy opinions about "Government should take measures to reduce differences in income levels." The main paper uses the perception questions about "A society to be fair, inequality needs to be low", "Country economy is doing well", and "Perceived percentage of unemployed". They are all reproduced in the Figure C.8. The same pattern outlined in the main paper appears if we consider other perception dimensions. For instance, if we consider the question "Large inequality is acceptable to reward effort", we see that the perception varies by income groups, and the differences in average preferences between income groups is larger among those that strongly agree with the statement. Moreover, the average support for redistribution is larger among those who disagree than those who agree. We can see that by the smaller values of the y-axis among the later.

The association between income groups, perceptions, and preferences are even stronger if we consider policy of providing basic income for all, measured by the question "Would you be against or in favor of having basic income scheme in your country". The Figure C.9 shows the results. Consider, for example, the perception that social benefit makes people lazy. Across income groups, those that strongly agree with that statement tend to oppose basic income schemes, but the proportion is larger among the rich.

The Figure C.11 shows how income groups and perceptions are related to the attitudes about the question "Government should spend more on education and training programs for the unemployed and less in benefit" and the same pattern emerges: the opinion about that policy changes by class and perceptions about the socioeconomic environment. Among the policies consiered here, the two that show less variation across class and perceptions are about ensuring standard of living for the old and ensuring living standard for the unemployed, displayed in the Figures C.12 and C.13, respectively.

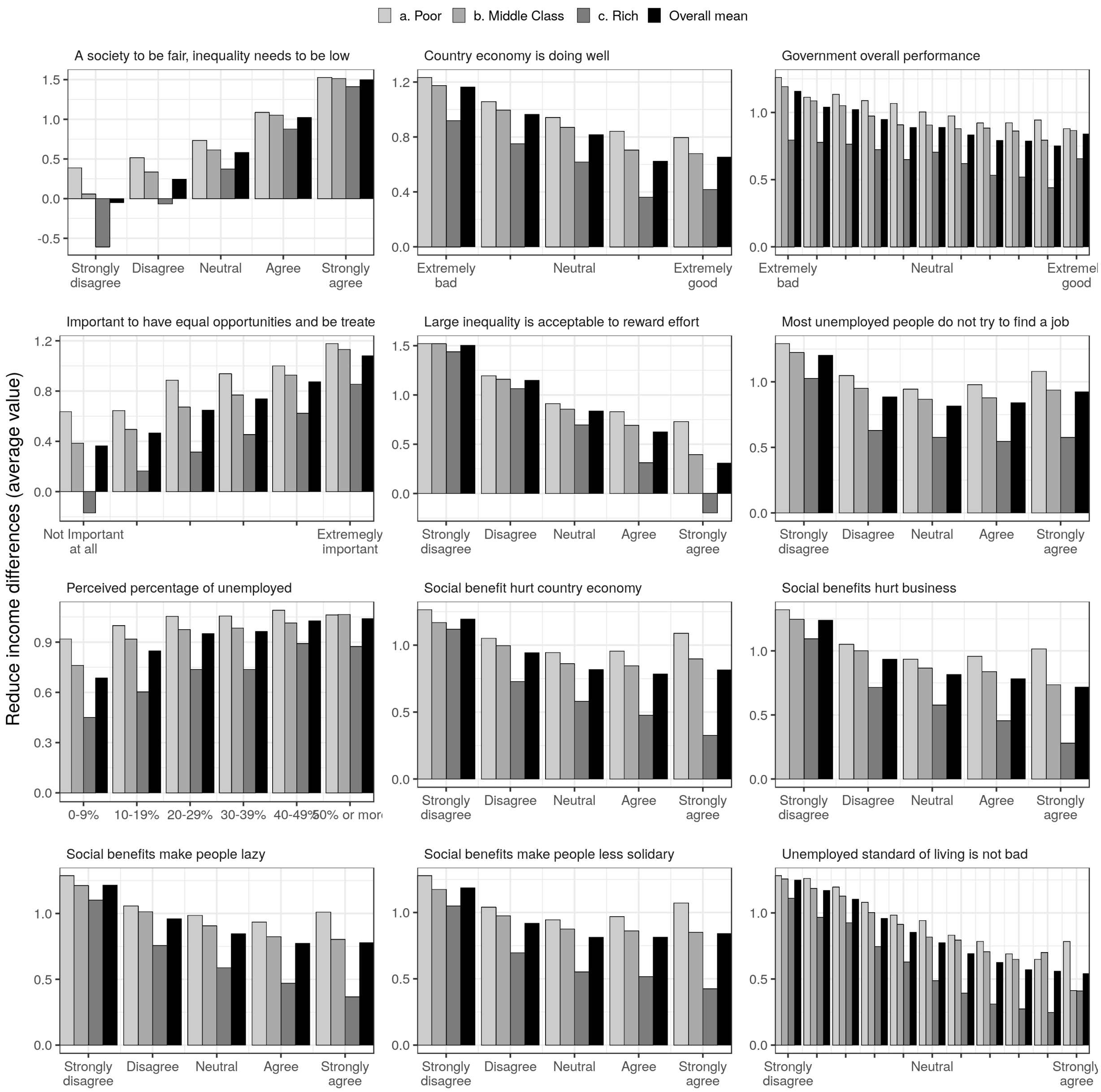


Figure C.8: Average support for redistribution by income and perception groups (policy 1)

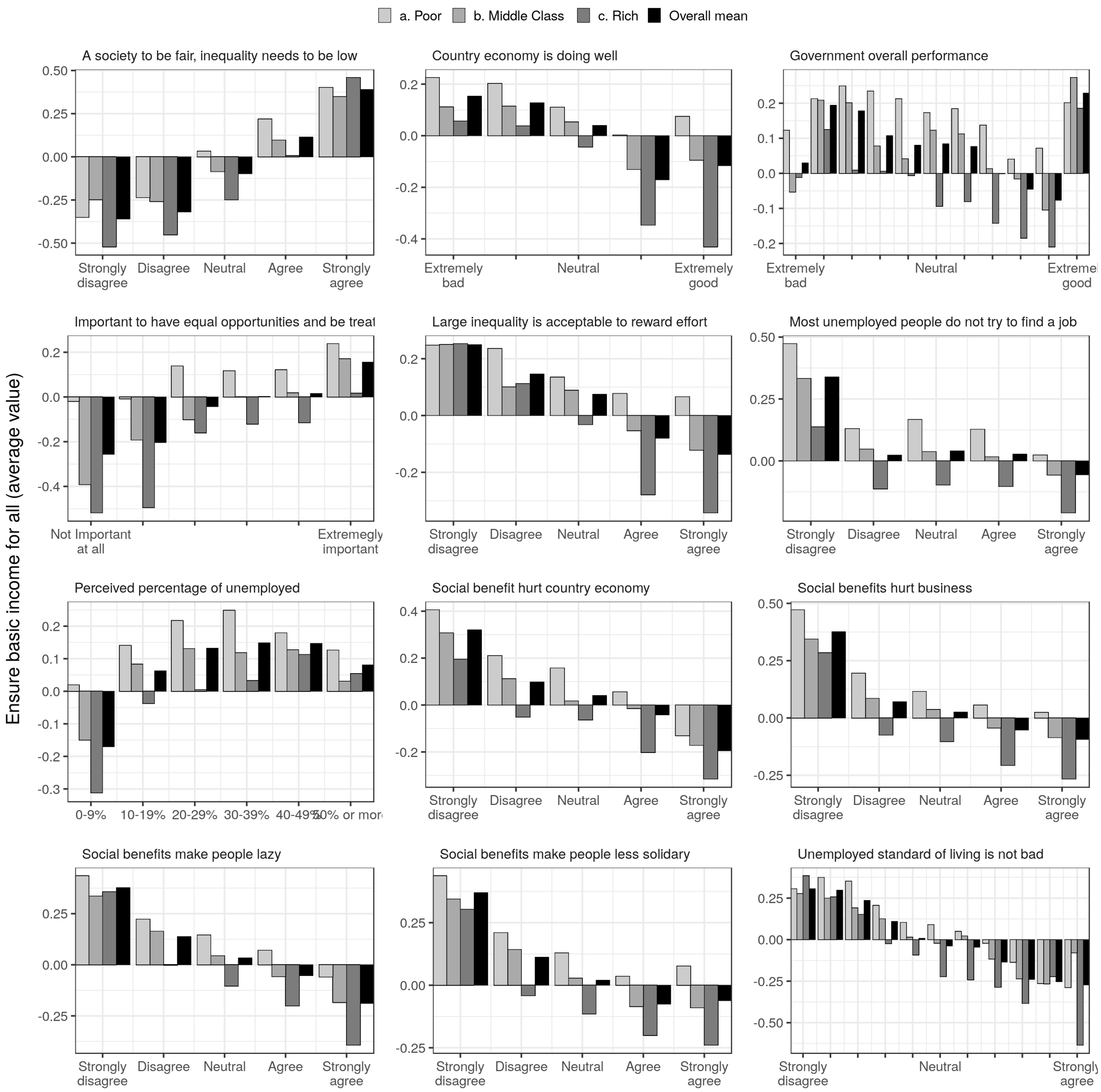


Figure C.9: Average support for redistribution by income and perception groups (policy 2)

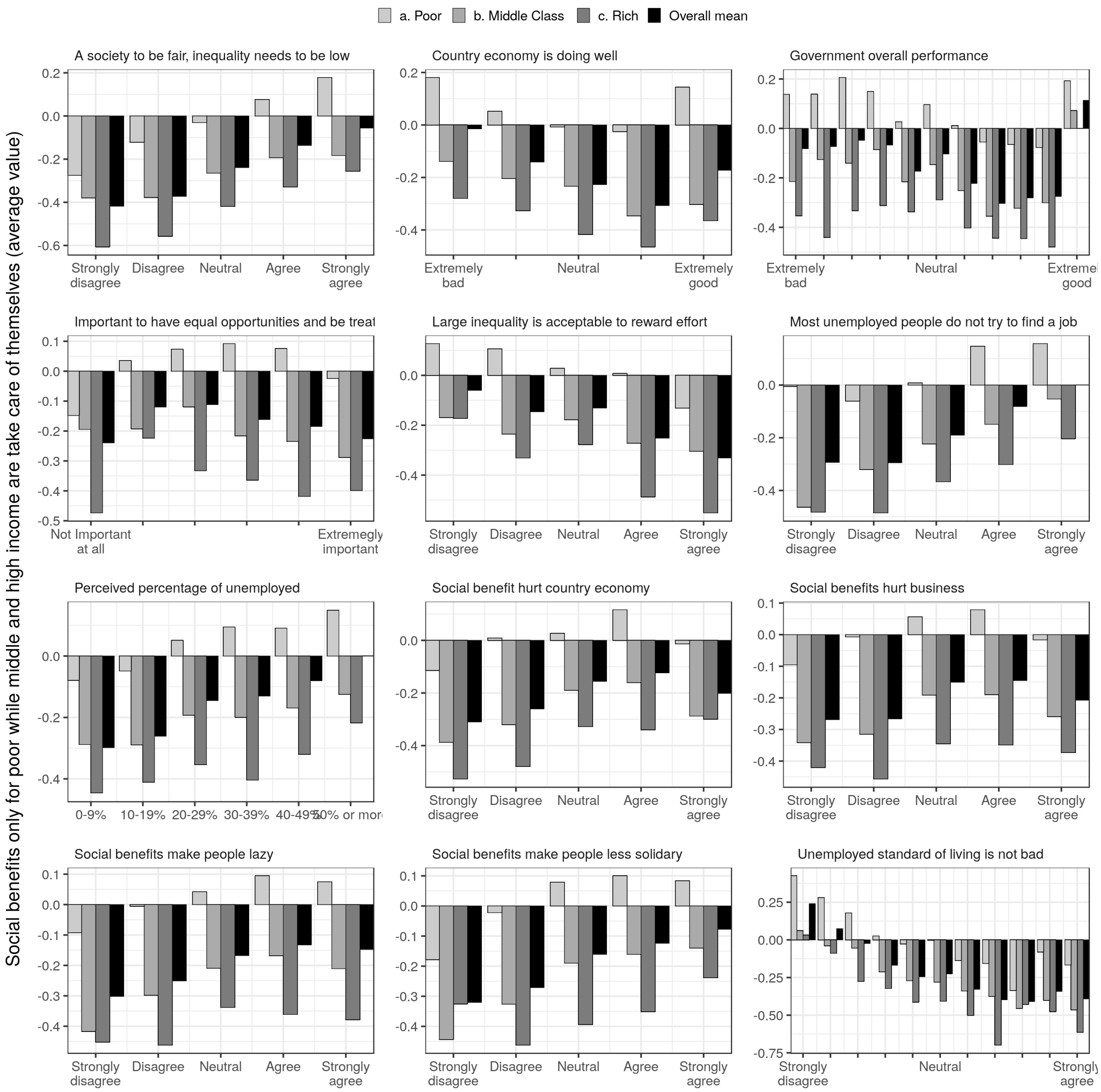


Figure C.10: Average support for redistribution by income and perception groups (policy 3)

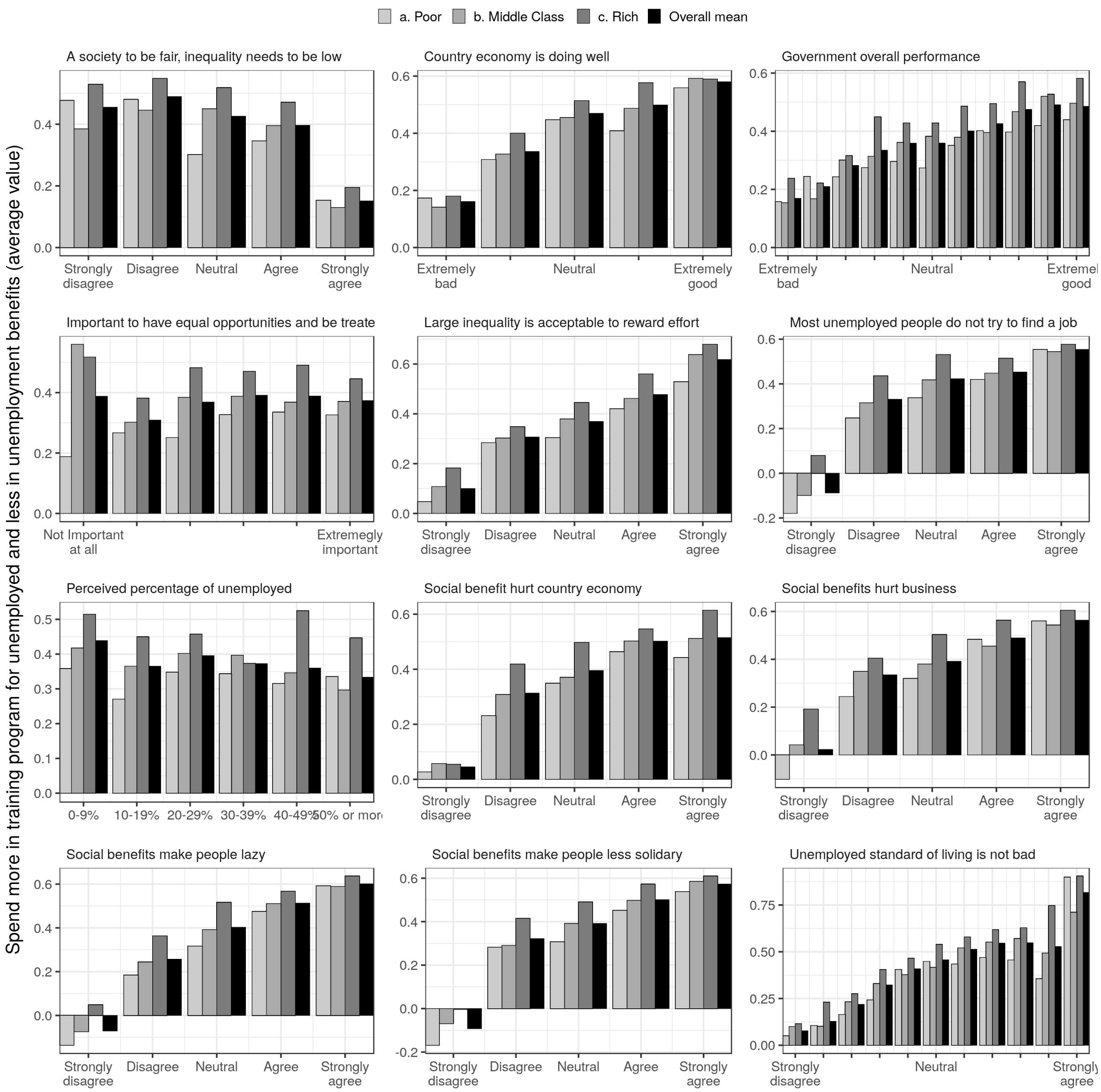


Figure C.11: Average support for redistribution by income and perception groups (policy 4)

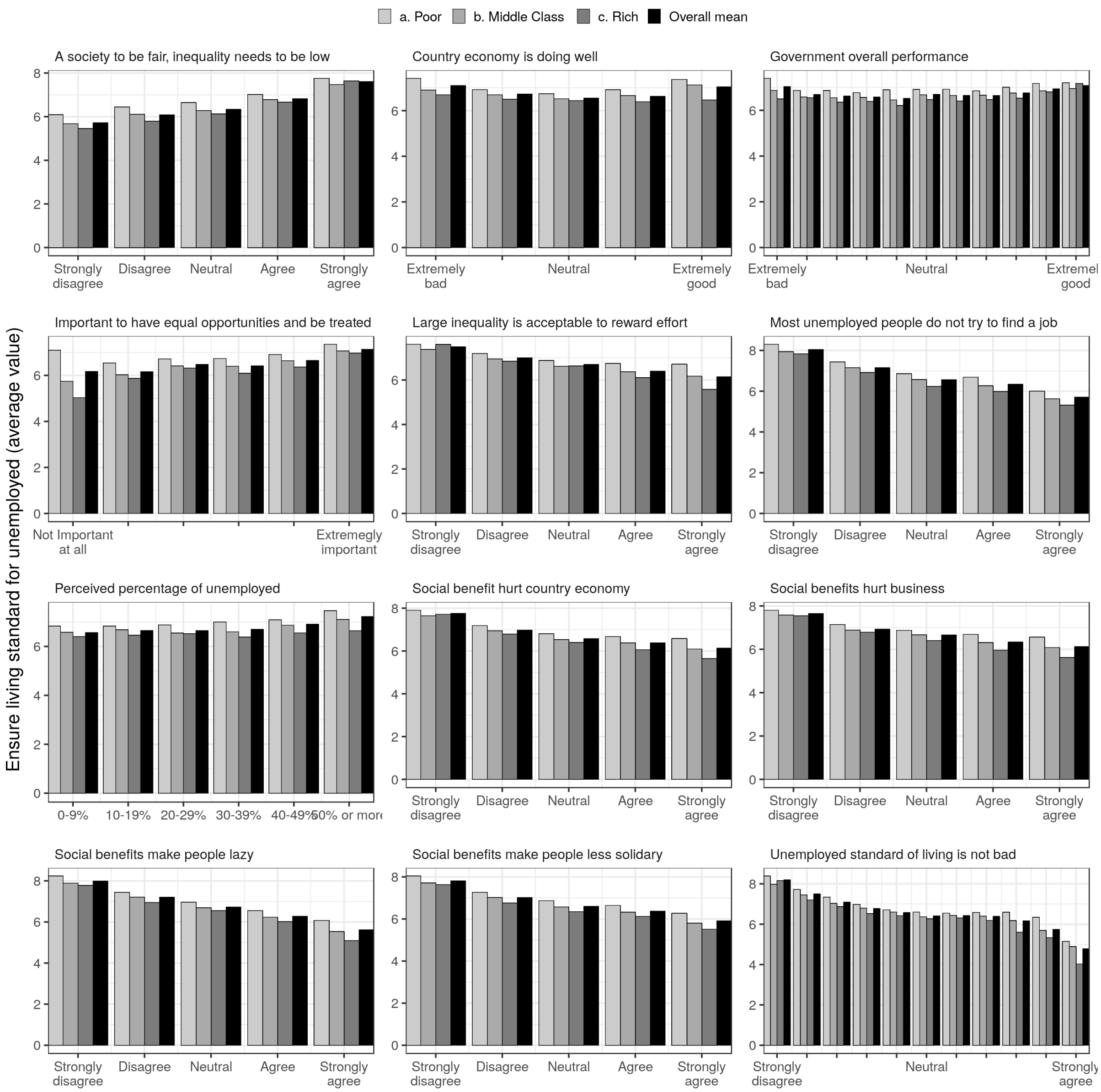


Figure C.12: Average support for redistribution by income and perception groups (policy 5)

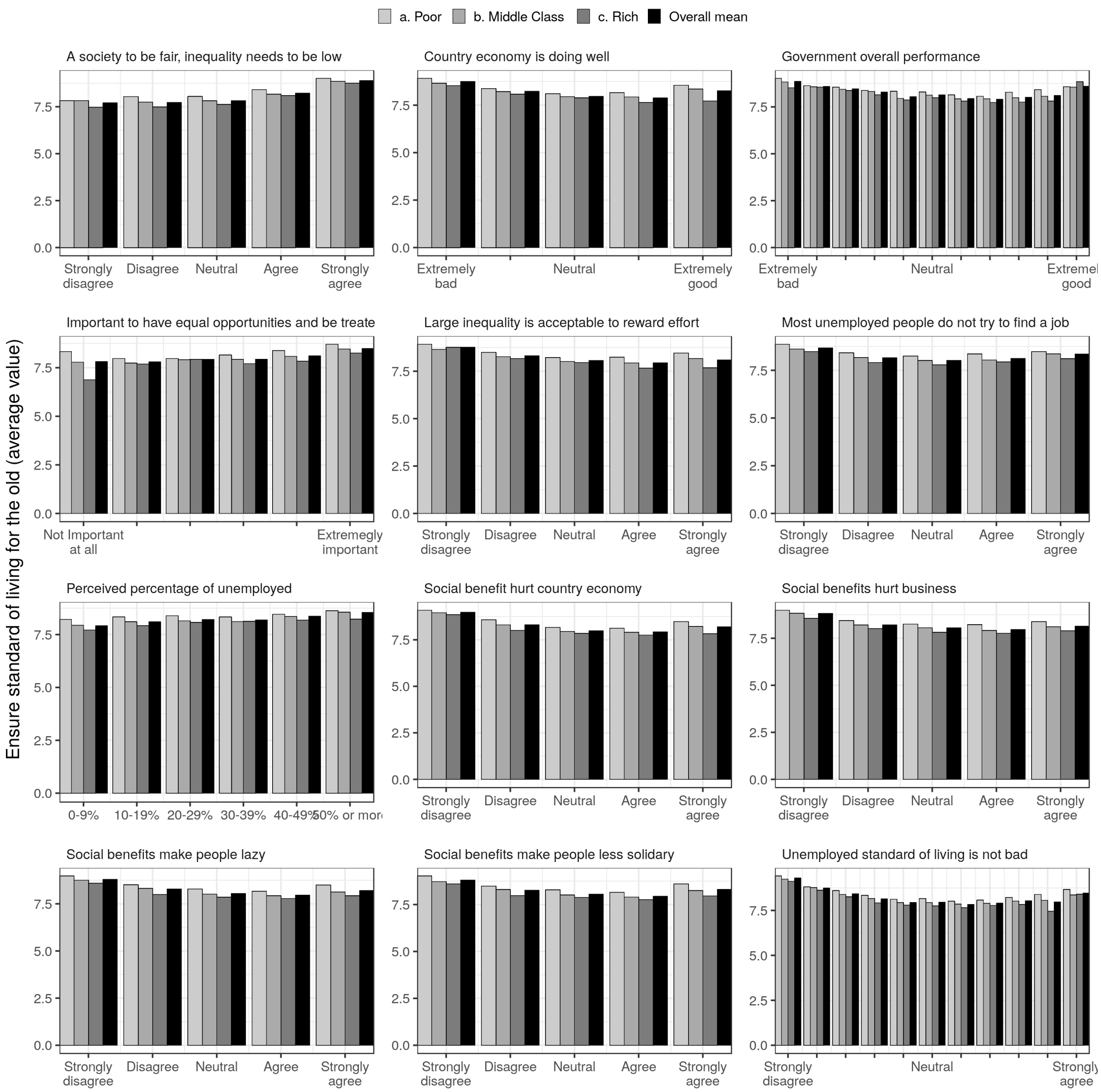


Figure C.13: Average support for redistribution by income and perception groups (policy 6)

C.2 Analyses

In the main paper, we estimated the reduced equation

$$\text{SfR}_{ij} = \lambda_0 + \lambda_1 \text{SEP}_{ij} + \lambda_{3:k}^T \text{controls}_{ij} + \varepsilon_{ij} \tag{C.1}$$

and the extensive form

$$\begin{aligned} \text{SfR}_{ij} &= \beta_0 + \beta_1 \text{SEP}_{ij} + \beta_2 \text{Perc}_{ij} + \beta_{3:k}^T \text{controls}_{ij} + \varepsilon_{ij} \\ \text{Perc}_{ij} &= \alpha_0 + \alpha_1 \text{SEP}_{ij} + \alpha_{3:k}^T \text{controls}_{ij} + \nu_{ij} \end{aligned} \tag{C.2}$$

where Perc indicates the measures of perceptions, and SfR a measure of support for redistribution. The quantities of interest are the proportion of the total effect of SEP on SfR that goes through perceptions $\left(\left|\frac{\beta_2\alpha_1}{\lambda_1}\right|\right)$, as well as λ_1, α_1, β_2, and $\beta_2\alpha_1$. The main paper focus on those quantities for some policies, perceptions, and some ways to construct the SEP. In the sections below, we extend the analysis for all policies, perceptions, and SEP indexes.

C.2.1 The Total Effect of socioeconomic positions (SEP) on preferences ($\hat{\lambda}_1$)

The Table C.6 shows the total effect of income ($\hat{\lambda}_1$) for all SEP indexes, and including or not the controls. We see that there is little variance across indexes and models. The results presented in the third column of the regression table of the main paper is in the seventh row of the third column, which shows the association between opinions about ensuring living standard for unemployed and SEP, constructed using income, education, and ISEI-08. The other result displayed in the seventh column of the regression table in the main paper is on the third row of the second column. We see that the conclusions wouldn't have changed substantially if we had used any one of the other measures of SEP. More details are in the following sections, which show the results for all the other quantities of interest.

Table C.6: Total effect of socioeconomic positions on preferences ($\hat{\lambda}_1$)

	No controls	All controls
Preference: Ensure basic income for all		
SEP (income)	-0.032 (-0.0369,-0.032)	-0.0406 (-0.0474,-0.0406)
SEP (income, educ)	-0.0559 (-0.0668,-0.0559)	-0.0612 (-0.0788,-0.0612)
SEP (income, educ, ISEC)	-0.0457 (-0.0547,-0.0457)	-0.0421 (-0.0559,-0.0421)
SEP (income, educ, ISEC, age)	-0.0317 (-0.0407,-0.0317)	-0.0148 (-0.0279,-0.0148)
Preference: Ensure living standard for unemployed		
SEP (income)	-0.0715 (-0.0798,-0.0715)	-0.0586 (-0.0699,-0.0586)
SEP (income, educ)	-0.1473 (-0.1658,-0.1473)	-0.0982 (-0.1272,-0.0982)
SEP (income, educ, ISEC)	-0.1169 (-0.1322,-0.1169)	-0.0578 (-0.0805,-0.0578)
SEP (income, educ, ISEC, age)	-0.1214 (-0.1368,-0.1214)	-0.0864 (-0.1079,-0.0864)
Preference: Ensure standard of living for the old		
SEP (income)	-0.053 (-0.0596,-0.053)	-0.0359 (-0.0451,-0.0359)
SEP (income, educ)	-0.1353 (-0.15,-0.1353)	-0.1104 (-0.1345,-0.1104)
SEP (income, educ, ISEC)	-0.111 (-0.1231,-0.111)	-0.1277 (-0.1465,-0.1277)
SEP (income, educ, ISEC, age)	-0.1274 (-0.1396,-0.1274)	-0.1339 (-0.1518,-0.1339)
Preference: Reduce income differences		
SEP (income)	-0.0534 (-0.0571,-0.0534)	-0.0394 (-0.0445,-0.0394)
SEP (income, educ)	-0.1095 (-0.1176,-0.1095)	-0.085 (-0.0981,-0.085)
SEP (income, educ, ISEC)	-0.0868 (-0.0935,-0.0868)	-0.0901 (-0.1003,-0.0901)
SEP (income, educ, ISEC, age)	-0.0921 (-0.0988,-0.0921)	-0.0917 (-0.1014,-0.0917)
Preference: Social benefits only for poor while middle and high income are take care of themselves		
SEP (income)	-0.0572 (-0.062,-0.0572)	-0.0319 (-0.0385,-0.0319)
SEP (income, educ)	-0.1537 (-0.1643,-0.1537)	-0.1037 (-0.1207,-0.1037)
SEP (income, educ, ISEC)	-0.1263 (-0.1351,-0.1263)	-0.1207 (-0.134,-0.1207)
SEP (income, educ, ISEC, age)	-0.1339 (-0.1427,-0.1339)	-0.1436 (-0.1563,-0.1436)
Preference: Spend more in training program for unemployed and less in unemployment benefits		
SEP (income)	0.0284 (0.0238,0.0284)	0.0222 (0.0159,0.0222)
SEP (income, educ)	0.0453 (0.0354,0.0453)	0.0339 (0.0179,0.0339)
SEP (income, educ, ISEC)	0.0388 (0.0306,0.0388)	0.0386 (0.026,0.0386)
SEP (income, educ, ISEC, age)	0.0416 (0.0333,0.0416)	0.0438 (0.0317,0.0438)

Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion

C.2.2 The association between SEP and perceptions ($\hat{\alpha}_1$)

The Table C.7 shows the value of the association between the four different ways to measure socioeconomic position (SEP) discussed in the paper and various perception dimensions ($\hat{\alpha}_1$). The first column of the table shows the perception dimension, the second to fifth columns shows the association when no controls are used, and the sixth to ninth columns shows the association after including the control variables. The results presented in the second column of the regression table in the main paper is in the Table C.4 on section C.1.3. The results presented in the fifth column of the regression table in the main paper is in the first row, eighth column of the Table C.7 (results may differ slightly due to NA values in the main table).

We can see that the association is robust across measures of SEP and different models.

Table C.7: Association ($\hat{\alpha}_1$) between socioeconomic position (SEP) and perceptions for varios measures of SEP and perception dimensions

	No controls				All controls			
Perception	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	-0.0363 (-0.0399, -0.0328)	-0.0778 (-0.0856, -0.0699)	-0.0612 (-0.0676, -0.0547)	-0.0676 (-0.0741, -0.0611)	-0.0299 (-0.0348, -0.025)	-0.0648 (-0.0774, -0.0522)	-0.0603 (-0.0701, -0.0504)	-0.0695 (-0.0788, -0.0601)
Can take active role in political issues	0.0813 (0.0775, 0.0852)	0.2723 (0.2641, 0.2805)	0.2274 (0.2207, 0.2342)	0.2362 (0.2295, 0.243)	0.0264 (0.0213, 0.0314)	0.1895 (0.1765, 0.2025)	0.2256 (0.2154, 0.2358)	0.2447 (0.235, 0.2544)
Confident that can participate in politics	0.0768 (0.0731, 0.0806)	0.2578 (0.2498, 0.2659)	0.2174 (0.2108, 0.224)	0.2244 (0.2177, 0.231)	0.0229 (0.018, 0.0278)	0.1755 (0.1628, 0.1883)	0.2141 (0.2041, 0.224)	0.2271 (0.2176, 0.2365)
Country economy is doing well	0.122 (0.1141, 0.1299)	0.2557 (0.2383, 0.2731)	0.2046 (0.1902, 0.2189)	0.2139 (0.1995, 0.2284)	0.0916 (0.0809, 0.1023)	0.2469 (0.2193, 0.2745)	0.2391 (0.2174, 0.2607)	0.2272 (0.2067, 0.2478)
Government overall performance	0.0654 (0.0558, 0.0749)	0.1297 (0.1087, 0.1508)	0.1045 (0.0872, 0.1218)	0.1105 (0.093, 0.128)	0.0476 (0.0345, 0.0608)	0.1616 (0.1276, 0.1957)	0.1526 (0.1259, 0.1792)	0.1306 (0.1052, 0.1559)
Important strong government to ensure safety	-0.025 (-0.0295, -0.0205)	-0.0727 (-0.0826, -0.0629)	-0.0589 (-0.067, -0.0508)	-0.0685 (-0.0767, -0.0604)	-0.0064 (-0.0126, -0.0002)	-0.0542 (-0.0701, -0.0383)	-0.0775 (-0.0899, -0.065)	-0.0892 (-0.101, -0.0774)
Important to be modest	-0.0441 (-0.0486, -0.0396)	-0.0995 (-0.1094, -0.0895)	-0.0791 (-0.0873, -0.071)	-0.0941 (-0.1024, -0.0859)	-0.0201 (-0.0262, -0.0139)	-0.0603 (-0.076, -0.0445)	-0.0655 (-0.0778, -0.0532)	-0.0821 (-0.0938, -0.0704)
Important to be rich	0.0388 (0.0337, 0.044)	0.1042 (0.093, 0.1155)	0.0766 (0.0673, 0.0858)	0.1102 (0.1009, 0.1196)	0.0076 (0.0005, 0.0146)	0.0367 (0.0187, 0.0546)	0.0265 (0.0124, 0.0406)	0.1047 (0.0911, 0.1183)
Important to be successful	0.0604 (0.0554, 0.0654)	0.1593 (0.1485, 0.1702)	0.1248 (0.1158, 0.1337)	0.1627 (0.1537, 0.1717)	0.0261 (0.0194, 0.0328)	0.0804 (0.0632, 0.0976)	0.0857 (0.0723, 0.0992)	0.1629 (0.15, 0.1758)
Important to have equal opportunities and be treated equally	-0.0051 (-0.0092, -0.0011)	0.0185 (0.0096, 0.0274)	0.0212 (0.0139, 0.0286)	0.0222 (0.0149, 0.0296)	-0.009 (-0.0144, -0.0036)	0.0086 (-0.0054, 0.0226)	0.0203 (0.0094, 0.0312)	0.0257 (0.0153, 0.0361)
Important to live in safe surroundings	-0.0305 (-0.0351, -0.0259)	-0.0742 (-0.0843, -0.0642)	-0.0577 (-0.0659, -0.0494)	-0.0681 (-0.0765, -0.0598)	-0.0015 (-0.0077, 0.0048)	-0.0431 (-0.0591, -0.0272)	-0.0659 (-0.0784, -0.0534)	-0.0821 (-0.0939, -0.0702)
Important to make autonomous decisions and be free	0.0138 (0.0097, 0.018)	0.0905 (0.0814, 0.0996)	0.0834 (0.0759, 0.0909)	0.0907 (0.0831, 0.0982)	-0.0118 (-0.0174, -0.0062)	0.0411 (0.0266, 0.0555)	0.0567 (0.0454, 0.068)	0.0632 (0.0525, 0.0739)
Large inequality is acceptable to reward effort	0.0336 (0.0294, 0.0378)	0.0585 (0.0493, 0.0677)	0.0442 (0.0367, 0.0518)	0.0468 (0.0391, 0.0544)	0.0327 (0.0268, 0.0385)	0.0519 (0.0369, 0.0668)	0.0466 (0.0349, 0.0583)	0.0482 (0.0371, 0.0594)
Likely to be unemployed soon	-0.084 (-0.0895, -0.0785)	-0.1513 (-0.1637, -0.139)	-0.1397 (-0.1497, -0.1297)	-0.1062 (-0.1165, -0.0959)	-0.0624 (-0.0691, -0.0557)	-0.1059 (-0.1235, -0.0883)	-0.1038 (-0.1175, -0.09)	-0.0316 (-0.0453, -0.0179)
Most unemployed people do not try to find a job	-0.0215 (-0.0256, -0.0175)	-0.1191 (-0.128, -0.1102)	-0.1045 (-0.1118, -0.0972)	-0.1094 (-0.1168, -0.102)	-0.0028 (-0.0084, 0.0028)	-0.1095 (-0.1238, -0.0951)	-0.1513 (-0.1625, -0.14)	-0.1416 (-0.1523, -0.131)
People like you can influence politics	0.0596 (0.0563, 0.0629)	0.1801 (0.173, 0.1872)	0.1488 (0.1429, 0.1546)	0.1556 (0.1497, 0.1615)	0.0267 (0.0223, 0.0311)	0.1289 (0.1176, 0.1403)	0.1515 (0.1426, 0.1604)	0.1646 (0.1562, 0.1731)
People like you have a say on what government does	0.0534 (0.05, 0.0568)	0.158 (0.1506, 0.1654)	0.1316 (0.1256, 0.1377)	0.1362 (0.1301, 0.1424)	0.0271 (0.0225, 0.0316)	0.1165 (0.1047, 0.1283)	0.1364 (0.1272, 0.1456)	0.1416 (0.1328, 0.1504)
Perceived percentage of unemployed	-0.0756 (-0.0791, -0.0721)	-0.2091 (-0.2168, -0.2014)	-0.1761 (-0.1824, -0.1698)	-0.1689 (-0.1753, -0.1625)	-0.0464 (-0.0511, -0.0418)	-0.1752 (-0.1872, -0.1632)	-0.1924 (-0.2019, -0.183)	-0.1655 (-0.1746, -0.1565)
Social benefits hurt business	0.0003 (-0.0037, 0.0044)	-0.0469 (-0.0558, -0.038)	-0.0452 (-0.0525, -0.0378)	-0.0472 (-0.0546, -0.0397)	0.0102 (0.0046, 0.0157)	-0.0314 (-0.0457, -0.0172)	-0.0692 (-0.0804, -0.058)	-0.0679 (-0.0786, -0.0572)
Social benefits hurt country economy	0.0108 (0.0068, 0.0148)	-0.0178 (-0.0266, -0.009)	-0.022 (-0.0293, -0.0148)	-0.0227 (-0.03, -0.0153)	0.02 (0.0145, 0.0256)	-0.0067 (-0.0209, 0.0075)	-0.0406 (-0.0517, -0.0295)	-0.0384 (-0.049, -0.0278)
Social benefits lead to equal society	-0.0003 (-0.0041, 0.0034)	0.0034 (-0.0049, 0.0117)	0.0067 (-0.0002, 0.0135)	0.0059 (-0.001, 0.0128)	-0.0017 (-0.0068, 0.0035)	0.0029 (-0.0103, 0.0161)	0.0164 (0.006, 0.0267)	0.0088 (-0.001, 0.0187)
Social benefits make people lazy	-0.0012 (-0.0054, 0.003)	-0.0546 (-0.0638, -0.0454)	-0.0527 (-0.0602, -0.0451)	-0.0559 (-0.0636, -0.0483)	0.0119 (0.0061, 0.0177)	-0.0541 (-0.069, -0.0392)	-0.0876 (-0.0992, -0.0759)	-0.0773 (-0.0884, -0.0662)
Social benefits make people less solidary	-0.0089 (-0.013, -0.0049)	-0.0705 (-0.0794, -0.0616)	-0.0636 (-0.0709, -0.0562)	-0.0714 (-0.0788, -0.064)	0.0045 (-0.0011, 0.0101)	-0.0599 (-0.0743, -0.0455)	-0.086 (-0.0973, -0.0747)	-0.0946 (-0.1053, -0.0839)
Social benefits prevent widespread poverty	0.0033 (-0.0004, 0.0071)	0.0226 (0.0144, 0.0307)	0.0228 (0.0161, 0.0295)	0.0172 (0.0104, 0.0239)	-0.0008 (-0.0058, 0.0042)	0.024 (0.0112, 0.0369)	0.0376 (0.0276, 0.0477)	0.02 (0.0104, 0.0296)
State of the education	0.0208 (0.0134, 0.0281)	-0.0028 (-0.019, 0.0134)	-0.0112 (-0.0245, 0.0021)	-0.0023 (-0.0158, 0.0111)	0.0226 (0.0126, 0.0327)	0.0114 (-0.0146, 0.0373)	0.0037 (-0.0166, 0.024)	0.0163 (-0.003, 0.0357)
State of the health services	0.0352 (0.0275, 0.0428)	0.0561 (0.0392, 0.0729)	0.0444 (0.0305, 0.0582)	0.0531 (0.0392, 0.0671)	0.0246 (0.0141, 0.0352)	0.0828 (0.0557, 0.11)	0.0796 (0.0583, 0.1009)	0.064 (0.0437, 0.0842)
Too few benefit to poor that are entitled	-0.0417 (-0.0454, -0.038)	-0.1099 (-0.118, -0.1017)	-0.0955 (-0.1022, -0.0888)	-0.0954 (-0.1022, -0.0886)	-0.0315 (-0.0367, -0.0264)	-0.0961 (-0.1094, -0.0829)	-0.1055 (-0.1159, -0.0951)	-0.0996 (-0.1095, -0.0898)
Too much benefits for many undeserving	-0.0156 (-0.0194, -0.0118)	-0.0814 (-0.0898, -0.0731)	-0.0723 (-0.0791, -0.0654)	-0.0802 (-0.0871, -0.0733)	0.0049 (-0.0003, 0.0101)	-0.06 (-0.0734, -0.0465)	-0.0952 (-0.1057, -0.0847)	-0.1011 (-0.1111, -0.0911)
Unemployed standard of living is not bad	0.0517 (0.0443, 0.0591)	0.0942 (0.0778, 0.1106)	0.0661 (0.0526, 0.0796)	0.0818 (0.0682, 0.0954)	0.0295 (0.0196, 0.0395)	0.0628 (0.0371, 0.0885)	0.0311 (0.0109, 0.0512)	0.0794 (0.0602, 0.0986)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

C.2.3 Effect of SEP ($\hat{\beta}_1$) and perceptions ($\hat{\beta}_2$) on welfare preferences

The Tables C.8 to C.13 present the association between SEP, perceptions, and welfare policy preferences for all measures of those variables. Consider the Table C.8. The sixth to ninth columns of the first row show the association of the perception that "a society to be fair, inequality needs to be low" and support for basic income schemes in the country. It does not matter how we measure SEP, that association is positive and stays around 0.2. The column eight of that row displays the results shown in the regression table of the main paper ($\hat{\beta}_2 = 0.206$). We can see that the results in the main paper do not change if we use different combinations of measures of SEP, policies, or perceptions.

Table C.8: Effect of socioeconomic position (SEP) ($\hat{\beta}_1$) and perception ($\hat{\beta}_2$) on welfare preference (Ensure basic income for all) for varios measures of SEP and perception dimensions.

	Effect of SEP on preferences given perceptions ($\hat{\beta}_1$)				Effect of perceptions on preferences given SEP ($\hat{\beta}_2$)			
Perception	SEP-1	SEP-2	SEP-3	SEP-4	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	-0.034 (-0.0408, -0.0273)	-0.0467 (-0.0642, -0.0293)	-0.0306 (-0.0443, -0.0168)	-0.0016 (-0.0147, 0.0115)	0.2098 (0.1926, 0.2271)	0.2055 (0.1895, 0.2214)	0.2061 (0.1902, 0.2221)	0.2038 (0.1879, 0.2198)
Can take active role in political issues	-0.0412 (-0.0481, -0.0344)	-0.0632 (-0.0812, -0.0453)	-0.0449 (-0.0592, -0.0305)	-0.0183 (-0.0321, -0.0045)	0.0171 (0.0002, 0.0339)	0.0195 (0.0038, 0.0351)	0.019 (0.0033, 0.0346)	0.0222 (0.0066, 0.0379)
Confident that can participate in politics	-0.0413 (-0.0481, -0.0345)	-0.0652 (-0.0831, -0.0473)	-0.0464 (-0.0607, -0.0321)	-0.0201 (-0.0338, -0.0064)	0.0233 (0.0059, 0.0406)	0.0269 (0.0109, 0.0429)	0.0265 (0.0105, 0.0425)	0.0285 (0.0124, 0.0445)
Country economy is doing well	-0.0406 (-0.0474, -0.0337)	-0.0606 (-0.0784, -0.0428)	-0.0419 (-0.0559, -0.0279)	-0.0143 (-0.0276, -0.001)	-0.0044 (-0.0125, 0.0036)	-0.0006 (-0.008, 0.0069)	-0.0011 (-0.0085, 0.0064)	-0.0017 (-0.0091, 0.0058)
Government overall performance	-0.0404 (-0.0474, -0.0335)	-0.0593 (-0.0773, -0.0412)	-0.0418 (-0.056, -0.0276)	-0.0146 (-0.0281, -0.001)	0.0064 (-0.0004, 0.0132)	0.0097 (0.0035, 0.016)	0.0095 (0.0033, 0.0158)	0.0092 (0.0029, 0.0154)
Important strong government to ensure safety	-0.0414 (-0.0482, -0.0345)	-0.0622 (-0.0799, -0.0445)	-0.0421 (-0.056, -0.0281)	-0.0153 (-0.0286, -0.002)	-0.0106 (-0.0244, 0.0033)	-0.011 (-0.0239, 0.0019)	-0.011 (-0.0239, 0.0019)	-0.0125 (-0.0254, 0.0004)
Important to be modest	-0.041 (-0.0479, -0.0342)	-0.0621 (-0.0798, -0.0444)	-0.0425 (-0.0564, -0.0286)	-0.0156 (-0.0289, -0.0023)	-0.0064 (-0.0203, 0.0076)	0.0008 (-0.0122, 0.0138)	0.001 (-0.0119, 0.014)	-0.0014 (-0.0144, 0.0116)
Important to be rich	-0.0412 (-0.048, -0.0344)	-0.0631 (-0.0807, -0.0454)	-0.0434 (-0.0573, -0.0295)	-0.02 (-0.0332, -0.0067)	0.041 (0.0288, 0.0531)	0.0427 (0.0314, 0.0541)	0.0425 (0.0311, 0.0538)	0.0511 (0.0399, 0.0623)
Important to be successful	-0.0413 (-0.0481, -0.0344)	-0.063 (-0.0807, -0.0454)	-0.0436 (-0.0575, -0.0297)	-0.0194 (-0.0327, -0.006)	0.0237 (0.011, 0.0365)	0.0242 (0.0123, 0.0361)	0.024 (0.0121, 0.0359)	0.0336 (0.0219, 0.0454)
Important to have equal opportunities and be treated equally	-0.04 (-0.0468, -0.0332)	-0.0619 (-0.0795, -0.0443)	-0.0439 (-0.0577, -0.0301)	-0.0169 (-0.0301, -0.0037)	0.0956 (0.0799, 0.1113)	0.0977 (0.0832, 0.1123)	0.0981 (0.0835, 0.1126)	0.0993 (0.0847, 0.1138)
Important to live in safe surroundings	-0.0412 (-0.0481, -0.0344)	-0.0636 (-0.0812, -0.0459)	-0.0441 (-0.058, -0.0302)	-0.0172 (-0.0304, -0.0039)	-0.0218 (-0.0354, -0.0081)	-0.0217 (-0.0345, -0.009)	-0.0219 (-0.0346, -0.0092)	-0.0246 (-0.0373, -0.0118)
Important to make autonomous decisions and be free	-0.0411 (-0.048, -0.0343)	-0.0618 (-0.0794, -0.0441)	-0.0415 (-0.0554, -0.0276)	-0.0144 (-0.0276, -0.0011)	-0.0065 (-0.0219, 0.0089)	-0.0066 (-0.0208, 0.0076)	-0.0064 (-0.0206, 0.0078)	-0.0065 (-0.0207, 0.0077)
Large inequality is acceptable to reward effort	-0.0376 (-0.0444, -0.0308)	-0.0563 (-0.0739, -0.0387)	-0.0376 (-0.0514, -0.0237)	-0.0102 (-0.0234, 0.003)	-0.0885 (-0.1031, -0.0739)	-0.0951 (-0.1087, -0.0815)	-0.0956 (-0.1091, -0.082)	-0.0948 (-0.1084, -0.0812)
Likely to be unemployed soon	-0.0402 (-0.0478, -0.0326)	-0.0531 (-0.0731, -0.0331)	-0.0284 (-0.0441, -0.0127)	-0.0106 (-0.026, 0.0047)	0.0385 (0.0227, 0.0543)	0.0455 (0.0308, 0.0601)	0.0462 (0.0315, 0.0608)	0.057 (0.0426, 0.0714)
Most unemployed people do not try to find a job	-0.0413 (-0.0481, -0.0345)	-0.0726 (-0.0903, -0.0549)	-0.0583 (-0.0723, -0.0443)	-0.0292 (-0.0426, -0.0159)	-0.1053 (-0.1207, -0.09)	-0.107 (-0.1213, -0.0928)	-0.1072 (-0.1214, -0.093)	-0.1043 (-0.1185, -0.0901)
People like you can influence politics	-0.0419 (-0.0487, -0.0351)	-0.0666 (-0.0844, -0.0488)	-0.0484 (-0.0625, -0.0342)	-0.0229 (-0.0364, -0.0093)	0.0529 (0.0335, 0.0723)	0.0569 (0.0389, 0.0749)	0.0563 (0.0383, 0.0743)	0.0604 (0.0425, 0.0784)
People like you have a say on what government does	-0.0416 (-0.0485, -0.0348)	-0.065 (-0.0827, -0.0472)	-0.0474 (-0.0615, -0.0332)	-0.0202 (-0.0337, -0.0067)	0.0486 (0.0299, 0.0673)	0.0521 (0.0347, 0.0694)	0.0516 (0.0343, 0.069)	0.0532 (0.0358, 0.0705)
Perceived percentage of unemployed	-0.0404 (-0.0473, -0.0335)	-0.0582 (-0.0764, -0.0401)	-0.0376 (-0.052, -0.0231)	-0.0095 (-0.0233, 0.0043)	0.0141 (-0.0048, 0.033)	0.0156 (-0.002, 0.0333)	0.0168 (-0.0008, 0.0344)	0.0255 (0.008, 0.0431)
Social benefits hurt business	-0.0407 (-0.0476, -0.0338)	-0.065 (-0.0829, -0.0472)	-0.0476 (-0.0617, -0.0334)	-0.0211 (-0.0346, -0.0075)	-0.1089 (-0.1248, -0.093)	-0.1134 (-0.1282, -0.0986)	-0.1141 (-0.1289, -0.0993)	-0.1141 (-0.1289, -0.0992)
Social benefits hurt country economy	-0.0394 (-0.0463, -0.0326)	-0.0631 (-0.0808, -0.0453)	-0.0453 (-0.0594, -0.0313)	-0.0185 (-0.0319, -0.0052)	-0.0994 (-0.1151, -0.0837)	-0.105 (-0.1196, -0.0903)	-0.1057 (-0.1204, -0.0911)	-0.1059 (-0.1206, -0.0913)
Social benefits lead to equal society	-0.0408 (-0.0477, -0.034)	-0.0623 (-0.08, -0.0446)	-0.0442 (-0.0581, -0.0303)	-0.0164 (-0.0296, -0.0032)	0.1233 (0.1066, 0.14)	0.121 (0.1055, 0.1365)	0.1213 (0.1058, 0.1368)	0.1205 (0.105, 0.1361)
Social benefits make people lazy	-0.0391 (-0.0458, -0.0323)	-0.0663 (-0.0838, -0.0487)	-0.0547 (-0.0686, -0.0408)	-0.0256 (-0.0388, -0.0124)	-0.1377 (-0.1523, -0.1231)	-0.1383 (-0.1519, -0.1247)	-0.1386 (-0.1522, -0.125)	-0.1357 (-0.1493, -0.1221)
Social benefits make people less solidary	-0.0401 (-0.0469, -0.0333)	-0.0656 (-0.0833, -0.0479)	-0.0513 (-0.0653, -0.0373)	-0.0249 (-0.0383, -0.0116)	-0.0882 (-0.1036, -0.0728)	-0.0868 (-0.1011, -0.0726)	-0.0871 (-0.1014, -0.0728)	-0.089 (-0.1033, -0.0747)
Social benefits prevent widespread poverty	-0.0411 (-0.0479, -0.0343)	-0.0632 (-0.0809, -0.0455)	-0.0453 (-0.0592, -0.0314)	-0.0171 (-0.0304, -0.0039)	0.0824 (0.0652, 0.0997)	0.0761 (0.0601, 0.092)	0.0763 (0.0603, 0.0923)	0.0728 (0.0568, 0.0887)
State of the education	-0.04 (-0.047, -0.033)	-0.0622 (-0.0804, -0.0439)	-0.0401 (-0.0545, -0.0258)	-0.0143 (-0.028, -0.0006)	0.0033 (-0.0058, 0.0124)	0.0076 (-0.0009, 0.016)	0.0075 (-0.001, 0.0159)	0.009 (0.0005, 0.0174)
State of the health services	-0.0409 (-0.0479, -0.0339)	-0.0605 (-0.0787, -0.0424)	-0.0412 (-0.0555, -0.0268)	-0.0142 (-0.0278, -0.0005)	-0.0083 (-0.017, 0.0004)	-0.0016 (-0.0097, 0.0064)	-0.0018 (-0.0098, 0.0062)	-0.0021 (-0.0102, 0.0059)
Too few benefit to poor that are entitled	-0.0391 (-0.0462, -0.032)	-0.0543 (-0.0726, -0.0359)	-0.031 (-0.0456, -0.0165)	-0.0056 (-0.0195, 0.0082)	0.1015 (0.0836, 0.1194)	0.1032 (0.0865, 0.1199)	0.104 (0.0873, 0.1207)	0.1054 (0.0887, 0.1221)
Too much benefits for many undeserving	-0.0398 (-0.0467, -0.0329)	-0.0677 (-0.0857, -0.0498)	-0.0511 (-0.0653, -0.037)	-0.0254 (-0.0389, -0.0119)	-0.1106 (-0.1274, -0.0937)	-0.1184 (-0.1341, -0.1027)	-0.1189 (-0.1346, -0.1033)	-0.1205 (-0.1362, -0.1048)
Unemployed standard of living is not bad	-0.0398 (-0.0466, -0.033)	-0.0603 (-0.078, -0.0426)	-0.0425 (-0.0564, -0.0286)	-0.0139 (-0.0272, -0.0006)	-0.0482 (-0.0568, -0.0395)	-0.0463 (-0.0543, -0.0383)	-0.0467 (-0.0546, -0.0387)	-0.0428 (-0.0508, -0.0348)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

Table C.9: Effect of socioeconomic position (SEP) ($\hat{\beta}_1$) and perception ($\hat{\beta}_2$) on welfare preference (Ensure living standard for unemployed) for varios measures of SEP and perception dimensions.

	Effect of SEP on preferences given perceptions ($\hat{\beta}_1$)				Effect of perceptions on preferences given SEP ($\hat{\beta}_2$)			
Perception	SEP-1	SEP-2	SEP-3	SEP-4	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	-0.0463	-0.069	-0.0296	-0.0547	0.4117	0.422	0.4229	0.4247
	(-0.0574, -0.0352)	(-0.0977, -0.0404)	(-0.052, -0.0072)	(-0.0761, -0.0333)	(0.3833, 0.4401)	(0.3959, 0.4482)	(0.3968, 0.4491)	(0.3986, 0.4508)
Can take active role in political issues	-0.0603	-0.1029	-0.0606	-0.0892	0.036	0.0198	0.0195	0.0149
	(-0.0716, -0.049)	(-0.1325, -0.0734)	(-0.0842, -0.037)	(-0.1118, -0.0666)	(0.0081, 0.0639)	(-0.006, 0.0457)	(-0.0063, 0.0454)	(-0.0109, 0.0407)
Confident that can participate in politics	-0.0596	-0.1018	-0.0599	-0.0887	0.023	0.0137	0.0137	0.0102
	(-0.0709, -0.0483)	(-0.1313, -0.0722)	(-0.0834, -0.0363)	(-0.1112, -0.0662)	(-0.0057, 0.0517)	(-0.0128, 0.0401)	(-0.0127, 0.0402)	(-0.0162, 0.0367)
Country economy is doing well	-0.0568	-0.0924	-0.0493	-0.0784	-0.0264	-0.0329	-0.0337	-0.0328
	(-0.0682, -0.0455)	(-0.1217, -0.0631)	(-0.0722, -0.0263)	(-0.1003, -0.0566)	(-0.0397, -0.0131)	(-0.0451, -0.0207)	(-0.0459, -0.0215)	(-0.045, -0.0206)
Government overall performance	-0.0591	-0.1008	-0.0576	-0.086	0.0135	0.0095	0.0091	0.0095
	(-0.0705, -0.0477)	(-0.1303, -0.0713)	(-0.0807, -0.0344)	(-0.108, -0.064)	(0.0024, 0.0246)	(-0.0007, 0.0197)	(-0.0011, 0.0193)	(-0.0007, 0.0197)
Important strong government to ensure safety	-0.0591	-0.0976	-0.05	-0.0771	0.1102	0.1196	0.1191	0.1192
	(-0.0704, -0.0478)	(-0.1267, -0.0684)	(-0.0728, -0.0271)	(-0.0988, -0.0553)	(0.0875, 0.133)	(0.0984, 0.1407)	(0.0979, 0.1403)	(0.098, 0.1403)
Important to be modest	-0.0582	-0.0955	-0.0545	-0.0811	0.0668	0.0906	0.0909	0.0928
	(-0.0695, -0.047)	(-0.1246, -0.0664)	(-0.0773, -0.0316)	(-0.1029, -0.0594)	(0.0438, 0.0899)	(0.0693, 0.112)	(0.0696, 0.1123)	(0.0715, 0.1141)
Important to be rich	-0.0598	-0.1027	-0.0602	-0.0904	0.0345	0.0419	0.0413	0.0295
	(-0.071, -0.0485)	(-0.1317, -0.0736)	(-0.083, -0.0374)	(-0.1122, -0.0687)	(0.0144, 0.0545)	(0.0232, 0.0605)	(0.0226, 0.06)	(0.0111, 0.0479)
Important to be successful	-0.0596	-0.1034	-0.0618	-0.0895	0.0085	0.0168	0.0164	0.005
	(-0.0709, -0.0483)	(-0.1325, -0.0743)	(-0.0847, -0.039)	(-0.1114, -0.0675)	(-0.0125, 0.0296)	(-0.0028, 0.0364)	(-0.0032, 0.036)	(-0.0143, 0.0243)
Important to have equal opportunities and be treated equally	-0.0569	-0.1023	-0.0654	-0.0952	0.2901	0.3028	0.3032	0.3012
	(-0.0681, -0.0458)	(-0.1311, -0.0736)	(-0.0879, -0.0429)	(-0.1166, -0.0738)	(0.2643, 0.3159)	(0.279, 0.3265)	(0.2795, 0.327)	(0.2775, 0.325)
Important to live in safe surroundings	-0.0598	-0.0995	-0.0567	-0.0842	0.0333	0.0484	0.0478	0.0499
	(-0.0711, -0.0485)	(-0.1286, -0.0705)	(-0.0795, -0.0339)	(-0.1059, -0.0625)	(0.0108, 0.0558)	(0.0274, 0.0694)	(0.0268, 0.0688)	(0.0289, 0.0709)
Important to make autonomous decisions and be free	-0.0594	-0.1039	-0.0623	-0.0907	0.0201	0.0519	0.0522	0.051
	(-0.0707, -0.0481)	(-0.133, -0.0748)	(-0.0851, -0.0395)	(-0.1124, -0.069)	(-0.0052, 0.0454)	(0.0286, 0.0751)	(0.029, 0.0755)	(0.0277, 0.0742)
Large inequality is acceptable to reward effort	-0.0504	-0.0819	-0.0415	-0.0694	-0.276	-0.2729	-0.2735	-0.2738
	(-0.0616, -0.0392)	(-0.1107, -0.053)	(-0.0641, -0.0189)	(-0.0909, -0.0479)	(-0.3, -0.252)	(-0.2951, -0.2506)	(-0.2958, -0.2512)	(-0.296, -0.2515)
Likely to be unemployed soon	-0.0559	-0.0716	-0.0285	-0.0545	0.0921	0.1048	0.1057	0.0918
	(-0.0684, -0.0434)	(-0.1044, -0.0388)	(-0.0542, -0.0028)	(-0.0795, -0.0295)	(0.0662, 0.118)	(0.0809, 0.1288)	(0.0818, 0.1296)	(0.0684, 0.1153)
Most unemployed people do not try to find a job	-0.0606	-0.1534	-0.1336	-0.1567	-0.5072	-0.5058	-0.5063	-0.5083
	(-0.0715, -0.0496)	(-0.1818, -0.125)	(-0.1561, -0.1112)	(-0.178, -0.1354)	(-0.5319, -0.4826)	(-0.5286, -0.483)	(-0.5291, -0.4835)	(-0.5311, -0.4855)
People like you can influence politics	-0.0599	-0.0997	-0.0586	-0.0876	0.0492	0.0261	0.0256	0.0197
	(-0.0712, -0.0486)	(-0.1291, -0.0703)	(-0.0819, -0.0354)	(-0.1099, -0.0654)	(0.0172, 0.0812)	(-0.0036, 0.0557)	(-0.0041, 0.0552)	(-0.0099, 0.0493)
People like you have a say on what government does	-0.0598	-0.1024	-0.0606	-0.0894	0.0595	0.0319	0.0316	0.0279
	(-0.0711, -0.0485)	(-0.1317, -0.073)	(-0.0838, -0.0374)	(-0.1115, -0.0673)	(0.0287, 0.0904)	(0.0033, 0.0606)	(0.0029, 0.0602)	(-0.0007, 0.0564)
Perceived percentage of unemployed	-0.057	-0.0837	-0.0383	-0.071	0.0568	0.0842	0.0858	0.0773
	(-0.0684, -0.0455)	(-0.1136, -0.0538)	(-0.0621, -0.0145)	(-0.0936, -0.0484)	(0.0257, 0.088)	(0.0553, 0.1131)	(0.0569, 0.1147)	(0.0486, 0.1061)
Social benefits hurt business	-0.0552	-0.1068	-0.0756	-0.1065	-0.3617	-0.3579	-0.3592	-0.3589
	(-0.0664, -0.0439)	(-0.136, -0.0775)	(-0.0987, -0.0525)	(-0.1285, -0.0845)	(-0.3877, -0.3358)	(-0.3822, -0.3336)	(-0.3835, -0.335)	(-0.3832, -0.3347)
Social benefits hurt country economy	-0.052	-0.1004	-0.0715	-0.0995	-0.36	-0.3619	-0.3632	-0.3631
	(-0.0632, -0.0408)	(-0.1294, -0.0714)	(-0.0943, -0.0487)	(-0.1212, -0.0778)	(-0.3856, -0.3343)	(-0.3858, -0.338)	(-0.3871, -0.3393)	(-0.387, -0.3392)
Social benefits lead to equal society	-0.0591	-0.098	-0.0581	-0.0853	0.2782	0.2799	0.2806	0.2817
	(-0.0703, -0.0479)	(-0.1269, -0.069)	(-0.0808, -0.0354)	(-0.1068, -0.0637)	(0.2508, 0.3056)	(0.2545, 0.3054)	(0.2552, 0.3061)	(0.2562, 0.3071)
Social benefits make people lazy	-0.0523	-0.1264	-0.1044	-0.1274	-0.532	-0.5287	-0.5294	-0.5318
	(-0.0632, -0.0415)	(-0.1545, -0.0983)	(-0.1264, -0.0823)	(-0.1484, -0.1065)	(-0.5554, -0.5086)	(-0.5505, -0.507)	(-0.5511, -0.5077)	(-0.5535, -0.5101)
Social benefits make people less solidary	-0.057	-0.1229	-0.094	-0.1255	-0.4093	-0.4049	-0.4055	-0.404
	(-0.0681, -0.0459)	(-0.1516, -0.0942)	(-0.1166, -0.0715)	(-0.147, -0.104)	(-0.4342, -0.3843)	(-0.428, -0.3817)	(-0.4286, -0.3823)	(-0.4271, -0.3808)
Social benefits prevent widespread poverty	-0.0595	-0.0992	-0.0624	-0.0889	0.178	0.1907	0.1911	0.1941
	(-0.0708, -0.0483)	(-0.1283, -0.0701)	(-0.0852, -0.0396)	(-0.1106, -0.0672)	(0.1496, 0.2064)	(0.1644, 0.2169)	(0.1648, 0.2174)	(0.1679, 0.2203)
State of the education	-0.0562	-0.0936	-0.0501	-0.0779	0.035	0.0364	0.0363	0.0346
	(-0.0677, -0.0447)	(-0.1233, -0.0638)	(-0.0734, -0.0269)	(-0.1001, -0.0557)	(0.0202, 0.0498)	(0.0227, 0.0502)	(0.0226, 0.05)	(0.0209, 0.0483)
State of the health services	-0.0588	-0.0972	-0.0557	-0.0821	0.0217	0.0261	0.0258	0.0261
	(-0.0702, -0.0474)	(-0.1267, -0.0677)	(-0.0789, -0.0325)	(-0.1042, -0.0601)	(0.0077, 0.0357)	(0.0131, 0.039)	(0.0128, 0.0388)	(0.0132, 0.0391)
Too few benefit to poor that are entitled	-0.0549	-0.0798	-0.0394	-0.0672	0.1817	0.1933	0.1939	0.1935
	(-0.0667, -0.0431)	(-0.1103, -0.0493)	(-0.0635, -0.0153)	(-0.0901, -0.0443)	(0.1518, 0.2116)	(0.1656, 0.221)	(0.1662, 0.2216)	(0.1658, 0.2212)
Too much benefits for many undeserving	-0.0569	-0.1168	-0.0852	-0.1159	-0.3321	-0.3111	-0.3121	-0.311
	(-0.0683, -0.0456)	(-0.1463, -0.0874)	(-0.1084, -0.062)	(-0.138, -0.0938)	(-0.3599, -0.3043)	(-0.3369, -0.2853)	(-0.338, -0.2863)	(-0.3368, -0.2852)
Unemployed standard of living is not bad	-0.0522	-0.0881	-0.0529	-0.0706	-0.2257	-0.2244	-0.2249	-0.226
	(-0.0632, -0.0411)	(-0.1168, -0.0595)	(-0.0753, -0.0305)	(-0.092, -0.0493)	(-0.2397, -0.2116)	(-0.2373, -0.2115)	(-0.2378, -0.2121)	(-0.2389, -0.2132)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

Table C.10: Effect of socioeconomic position (SEP) ($\hat{\beta}_1$) and perception ($\hat{\beta}_2$) on welfare preference (Ensure standard of living for the old) for varios measures of SEP and perception dimensions.

	Effect of SEP on preferences given perceptions ($\hat{\beta}_1$)				Effect of perceptions on preferences given SEP ($\hat{\beta}_2$)			
Perception	SEP-1	SEP-2	SEP-3	SEP-4	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	-0.0268 (-0.0361, -0.0176)	-0.0904 (-0.1143, -0.0665)	-0.11 (-0.1287, -0.0912)	-0.1133 (-0.1311, -0.0955)	0.2938 (0.2702, 0.3174)	0.3031 (0.2813, 0.325)	0.3034 (0.2816, 0.3253)	0.3012 (0.2794, 0.323)
Can take active role in political issues	-0.0352 (-0.0445, -0.0259)	-0.1029 (-0.1274, -0.0784)	-0.1194 (-0.139, -0.0998)	-0.1251 (-0.1438, -0.1064)	-0.0353 (-0.0583, -0.0122)	-0.0379 (-0.0594, -0.0165)	-0.0385 (-0.0599, -0.017)	-0.0359 (-0.0573, -0.0145)
Confident that can participate in politics	-0.0347 (-0.0441, -0.0254)	-0.105 (-0.1296, -0.0805)	-0.1221 (-0.1417, -0.1026)	-0.1285 (-0.1472, -0.1099)	-0.0251 (-0.0488, -0.0013)	-0.0249 (-0.0469, -0.003)	-0.0254 (-0.0473, -0.0034)	-0.0226 (-0.0445, -0.0007)
Country economy is doing well	-0.0294 (-0.0387, -0.02)	-0.0916 (-0.1159, -0.0674)	-0.1077 (-0.1267, -0.0887)	-0.115 (-0.1331, -0.097)	-0.0748 (-0.0858, -0.0639)	-0.0776 (-0.0877, -0.0675)	-0.0779 (-0.088, -0.0678)	-0.0775 (-0.0875, -0.0674)
Government overall performance	-0.031 (-0.0404, -0.0216)	-0.1008 (-0.1252, -0.0764)	-0.1169 (-0.136, -0.0978)	-0.125 (-0.1431, -0.1068)	-0.0572 (-0.0664, -0.0481)	-0.0581 (-0.0665, -0.0496)	-0.0582 (-0.0666, -0.0498)	-0.0584 (-0.0668, -0.05)
Important strong government to ensure safety	-0.036 (-0.0452, -0.0267)	-0.1016 (-0.1255, -0.0777)	-0.1125 (-0.1313, -0.0938)	-0.1153 (-0.1331, -0.0975)	0.2187 (0.2001, 0.2373)	0.2254 (0.2081, 0.2428)	0.2256 (0.2083, 0.243)	0.2243 (0.2069, 0.2416)
Important to be modest	-0.0352 (-0.0445, -0.0259)	-0.1039 (-0.128, -0.0798)	-0.123 (-0.1419, -0.1042)	-0.1271 (-0.1451, -0.1092)	0.0881 (0.0691, 0.1071)	0.0998 (0.0821, 0.1174)	0.1001 (0.0824, 0.1177)	0.0991 (0.0815, 0.1167)
Important to be rich	-0.0374 (-0.0467, -0.0281)	-0.1128 (-0.1369, -0.0887)	-0.1318 (-0.1507, -0.1129)	-0.1407 (-0.1587, -0.1227)	0.0264 (0.0099, 0.043)	0.0366 (0.0211, 0.0521)	0.0366 (0.0211, 0.0521)	0.0377 (0.0225, 0.0529)
Important to be successful	-0.0366 (-0.0459, -0.0273)	-0.112 (-0.1362, -0.0879)	-0.1321 (-0.151, -0.1131)	-0.1392 (-0.1573, -0.1211)	-0.0001 (-0.0175, 0.0172)	0.0133 (-0.0029, 0.0295)	0.0133 (-0.0029, 0.0295)	0.0158 (-0.0001, 0.0318)
Important to have equal opportunities and be treated equally	-0.035 (-0.0442, -0.0258)	-0.1129 (-0.1368, -0.0891)	-0.1349 (-0.1535, -0.1162)	-0.142 (-0.1597, -0.1243)	0.229 (0.2077, 0.2503)	0.2444 (0.2248, 0.2641)	0.2445 (0.2248, 0.2641)	0.244 (0.2244, 0.2637)
Important to live in safe surroundings	-0.0375 (-0.0468, -0.0282)	-0.1056 (-0.1296, -0.0815)	-0.1216 (-0.1404, -0.1028)	-0.126 (-0.1439, -0.1081)	0.1164 (0.0978, 0.135)	0.1312 (0.1139, 0.1485)	0.1314 (0.1141, 0.1487)	0.13 (0.1127, 0.1473)
Important to make autonomous decisions and be free	-0.0357 (-0.045, -0.0264)	-0.1155 (-0.1396, -0.0915)	-0.1368 (-0.1556, -0.1179)	-0.1437 (-0.1616, -0.1258)	0.1038 (0.083, 0.1246)	0.1327 (0.1135, 0.1519)	0.1329 (0.1137, 0.1521)	0.1336 (0.1144, 0.1527)
Large inequality is acceptable to reward effort	-0.0316 (-0.0409, -0.0223)	-0.1022 (-0.1263, -0.0781)	-0.1203 (-0.1392, -0.1014)	-0.1262 (-0.1441, -0.1082)	-0.146 (-0.1659, -0.126)	-0.1426 (-0.1612, -0.124)	-0.1428 (-0.1614, -0.1241)	-0.1422 (-0.1608, -0.1236)
Likely to be unemployed soon	-0.036 (-0.0463, -0.0257)	-0.1053 (-0.1325, -0.0781)	-0.1282 (-0.1495, -0.1069)	-0.1358 (-0.1566, -0.1151)	0.006 (-0.0153, 0.0273)	0.0083 (-0.0115, 0.0282)	0.0086 (-0.0112, 0.0285)	0.0117 (-0.0077, 0.0311)
Most unemployed people do not try to find a job	-0.0364 (-0.0458, -0.0271)	-0.1202 (-0.1445, -0.0958)	-0.1401 (-0.1593, -0.1209)	-0.1454 (-0.1636, -0.1272)	-0.0682 (-0.0892, -0.0472)	-0.0754 (-0.0949, -0.0559)	-0.075 (-0.0945, -0.0555)	-0.0762 (-0.0956, -0.0567)
People like you can influence politics	-0.0311 (-0.0404, -0.0218)	-0.0849 (-0.1092, -0.0605)	-0.0977 (-0.1169, -0.0785)	-0.1022 (-0.1205, -0.0839)	-0.1825 (-0.2089, -0.1562)	-0.1935 (-0.2181, -0.169)	-0.1943 (-0.2188, -0.1697)	-0.1912 (-0.2157, -0.1668)
People like you have a say on what government does	-0.0315 (-0.0408, -0.0222)	-0.0917 (-0.116, -0.0675)	-0.1034 (-0.1225, -0.0842)	-0.1091 (-0.1273, -0.0909)	-0.169 (-0.1944, -0.1436)	-0.1826 (-0.2063, -0.159)	-0.1832 (-0.2069, -0.1596)	-0.1818 (-0.2053, -0.1582)
Perceived percentage of unemployed	-0.031 (-0.0405, -0.0216)	-0.0914 (-0.1162, -0.0666)	-0.1049 (-0.1247, -0.0852)	-0.1141 (-0.1328, -0.0954)	0.1148 (0.0891, 0.1405)	0.1287 (0.1048, 0.1527)	0.1295 (0.1055, 0.1534)	0.1284 (0.1046, 0.1522)
Social benefits hurt business	-0.033 (-0.0425, -0.0236)	-0.1132 (-0.1378, -0.0886)	-0.139 (-0.1584, -0.1197)	-0.145 (-0.1635, -0.1266)	-0.1547 (-0.1764, -0.133)	-0.1554 (-0.1758, -0.1351)	-0.1555 (-0.1758, -0.1351)	-0.1552 (-0.1755, -0.1348)
Social benefits hurt country economy	-0.0322 (-0.0416, -0.0229)	-0.1117 (-0.1361, -0.0873)	-0.1348 (-0.154, -0.1157)	-0.1398 (-0.158, -0.1216)	-0.1718 (-0.1933, -0.1504)	-0.1762 (-0.1963, -0.1562)	-0.1763 (-0.1964, -0.1563)	-0.1759 (-0.1959, -0.1559)
Social benefits lead to equal society	-0.0344 (-0.0437, -0.0251)	-0.1071 (-0.1313, -0.0828)	-0.127 (-0.146, -0.108)	-0.1321 (-0.1502, -0.1141)	0.0549 (0.0321, 0.0778)	0.0572 (0.0359, 0.0786)	0.0572 (0.0359, 0.0785)	0.0565 (0.0353, 0.0778)
Social benefits make people lazy	-0.0339 (-0.0432, -0.0246)	-0.117 (-0.1412, -0.0929)	-0.1396 (-0.1585, -0.1207)	-0.1444 (-0.1624, -0.1264)	-0.1244 (-0.1444, -0.1043)	-0.1258 (-0.1445, -0.1072)	-0.1255 (-0.1442, -0.1069)	-0.1263 (-0.1449, -0.1077)
Social benefits make people less solidary	-0.035 (-0.0444, -0.0257)	-0.1188 (-0.143, -0.0945)	-0.1399 (-0.159, -0.1209)	-0.1469 (-0.1651, -0.1288)	-0.1094 (-0.1304, -0.0884)	-0.1124 (-0.132, -0.0929)	-0.1123 (-0.1319, -0.0928)	-0.1137 (-0.1332, -0.0942)
Social benefits prevent widespread poverty	-0.0354 (-0.0448, -0.0261)	-0.11 (-0.1343, -0.0858)	-0.1303 (-0.1493, -0.1113)	-0.1352 (-0.1532, -0.1172)	0.0484 (0.0249, 0.072)	0.0643 (0.0424, 0.0861)	0.0642 (0.0423, 0.086)	0.063 (0.0412, 0.0848)
State of the education	-0.0321 (-0.0417, -0.0225)	-0.1047 (-0.1295, -0.0799)	-0.1227 (-0.1421, -0.1033)	-0.1275 (-0.146, -0.1091)	0.0018 (-0.0105, 0.0141)	-0.0008 (-0.0123, 0.0106)	-0.001 (-0.0124, 0.0105)	-0.001 (-0.0124, 0.0105)
State of the health services	-0.0338 (-0.0433, -0.0244)	-0.1072 (-0.1318, -0.0826)	-0.1222 (-0.1415, -0.1029)	-0.1282 (-0.1465, -0.1099)	-0.0342 (-0.0458, -0.0226)	-0.0326 (-0.0434, -0.0218)	-0.0328 (-0.0436, -0.022)	-0.0332 (-0.044, -0.0224)
Too few benefit to poor that are entitled	-0.0327 (-0.0424, -0.023)	-0.0971 (-0.1223, -0.0719)	-0.1101 (-0.13, -0.0902)	-0.1159 (-0.1347, -0.097)	0.1807 (0.1561, 0.2052)	0.1772 (0.1543, 0.2001)	0.1777 (0.1548, 0.2006)	0.1775 (0.1547, 0.2004)
Too much benefits for many undeserving	-0.0373 (-0.0467, -0.0278)	-0.1097 (-0.1344, -0.085)	-0.1215 (-0.141, -0.1021)	-0.1276 (-0.1461, -0.1091)	0.0634 (0.0402, 0.0866)	0.0743 (0.0527, 0.0959)	0.0745 (0.0529, 0.0961)	0.0735 (0.0519, 0.0951)
Unemployed standard of living is not bad	-0.0342 (-0.0436, -0.0249)	-0.1088 (-0.133, -0.0847)	-0.1271 (-0.146, -0.1082)	-0.1293 (-0.1472, -0.1113)	-0.084 (-0.0958, -0.0722)	-0.0845 (-0.0954, -0.0737)	-0.0845 (-0.0954, -0.0737)	-0.0826 (-0.0934, -0.0718)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

Table C.11: Effect of socioeconomic position (SEP) ($\hat{\beta}_1$) and perception ($\hat{\beta}_2$) on welfare preference (Reduce income differences) for varios measures of SEP and perception dimensions.

	Effect of SEP on preferences given perceptions ($\hat{\beta}_1$)				Effect of perceptions on preferences given SEP ($\hat{\beta}_2$)			
Perception	SEP-1	SEP-2	SEP-3	SEP-4	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	-0.0281 (-0.0329, -0.0234)	-0.0604 (-0.0727, -0.0482)	-0.0669 (-0.0764, -0.0573)	-0.0652 (-0.0743, -0.0561)	0.3781 (0.366, 0.3903)	0.3821 (0.3709, 0.3932)	0.3823 (0.3712, 0.3935)	0.3824 (0.3712, 0.3935)
Can take active role in political issues	-0.0399 (-0.045, -0.0348)	-0.0865 (-0.0999, -0.0731)	-0.0916 (-0.1022, -0.0809)	-0.0928 (-0.103, -0.0826)	0.0013 (-0.0114, 0.0139)	0.0046 (-0.0071, 0.0163)	0.0043 (-0.0074, 0.016)	0.0024 (-0.0092, 0.0141)
Confident that can participate in politics	-0.0391 (-0.0443, -0.034)	-0.0843 (-0.0976, -0.0709)	-0.0895 (-0.1001, -0.0788)	-0.0909 (-0.1011, -0.0808)	-0.0128 (-0.0258, 0.0001)	-0.0072 (-0.0191, 0.0048)	-0.0074 (-0.0193, 0.0046)	-0.0085 (-0.0204, 0.0034)
Country economy is doing well	-0.0349 (-0.04, -0.0297)	-0.0734 (-0.0866, -0.0602)	-0.0783 (-0.0886, -0.0679)	-0.0805 (-0.0903, -0.0706)	-0.0481 (-0.0541, -0.0421)	-0.0487 (-0.0542, -0.0432)	-0.049 (-0.0544, -0.0435)	-0.0492 (-0.0547, -0.0437)
Government overall performance	-0.0398 (-0.045, -0.0346)	-0.0847 (-0.0981, -0.0713)	-0.0875 (-0.098, -0.0771)	-0.09 (-0.1, -0.08)	-0.0222 (-0.0272, -0.0171)	-0.0242 (-0.0288, -0.0196)	-0.0244 (-0.029, -0.0198)	-0.0246 (-0.0292, -0.02)
Important strong government to ensure safety	-0.0397 (-0.0448, -0.0346)	-0.0843 (-0.0974, -0.0711)	-0.0879 (-0.0983, -0.0776)	-0.0893 (-0.0992, -0.0795)	0.0397 (0.0293, 0.05)	0.0404 (0.0309, 0.05)	0.0405 (0.0309, 0.0501)	0.0405 (0.031, 0.0501)
Important to be modest	-0.0389 (-0.044, -0.0338)	-0.0832 (-0.0963, -0.0701)	-0.0874 (-0.0976, -0.0771)	-0.0883 (-0.0981, -0.0786)	0.0514 (0.041, 0.0619)	0.0579 (0.0483, 0.0675)	0.0581 (0.0485, 0.0678)	0.0585 (0.0489, 0.0681)
Important to be rich	-0.04 (-0.0451, -0.0349)	-0.0867 (-0.0998, -0.0736)	-0.0916 (-0.1019, -0.0812)	-0.0926 (-0.1024, -0.0828)	-0.0112 (-0.0202, -0.0021)	-0.0066 (-0.0151, 0.0018)	-0.0067 (-0.0152, 0.0017)	-0.0079 (-0.0162, 0.0004)
Important to be successful	-0.039 (-0.0441, -0.0339)	-0.0835 (-0.0966, -0.0703)	-0.0882 (-0.0986, -0.0779)	-0.0876 (-0.0974, -0.0777)	-0.0361 (-0.0457, -0.0266)	-0.033 (-0.0418, -0.0241)	-0.0331 (-0.0419, -0.0242)	-0.0335 (-0.0423, -0.0248)
Important to have equal opportunities and be treated equally	-0.0384 (-0.0435, -0.0334)	-0.0872 (-0.1002, -0.0742)	-0.0936 (-0.1037, -0.0834)	-0.0962 (-0.1058, -0.0865)	0.1416 (0.1299, 0.1532)	0.1439 (0.1333, 0.1546)	0.144 (0.1333, 0.1547)	0.1436 (0.1329, 0.1543)
Important to live in safe surroundings	-0.04 (-0.0451, -0.0349)	-0.0849 (-0.0981, -0.0718)	-0.0896 (-0.0999, -0.0793)	-0.091 (-0.1008, -0.0813)	0.0198 (0.0096, 0.03)	0.0232 (0.0138, 0.0327)	0.0233 (0.0138, 0.0328)	0.0241 (0.0146, 0.0335)
Important to make autonomous decisions and be free	-0.0399 (-0.045, -0.0348)	-0.087 (-0.1002, -0.0739)	-0.0923 (-0.1026, -0.082)	-0.0942 (-0.104, -0.0844)	0.0086 (-0.0028, 0.0201)	0.0221 (0.0116, 0.0326)	0.0223 (0.0118, 0.0328)	0.022 (0.0115, 0.0324)
Large inequality is acceptable to reward effort	-0.0316 (-0.0365, -0.0267)	-0.0722 (-0.0849, -0.0596)	-0.0784 (-0.0883, -0.0685)	-0.0796 (-0.089, -0.0702)	-0.2464 (-0.2569, -0.2358)	-0.246 (-0.2558, -0.2363)	-0.2462 (-0.256, -0.2365)	-0.2464 (-0.2561, -0.2367)
Likely to be unemployed soon	-0.0377 (-0.0434, -0.0319)	-0.079 (-0.094, -0.064)	-0.0896 (-0.1013, -0.0778)	-0.0932 (-0.1047, -0.0818)	0.0318 (0.02, 0.0437)	0.0376 (0.0266, 0.0485)	0.0379 (0.027, 0.0489)	0.0363 (0.0256, 0.047)
Most unemployed people do not try to find a job	-0.04 (-0.0451, -0.0349)	-0.0928 (-0.106, -0.0796)	-0.1008 (-0.1112, -0.0904)	-0.1015 (-0.1114, -0.0916)	-0.0687 (-0.0802, -0.0573)	-0.0679 (-0.0785, -0.0574)	-0.0678 (-0.0784, -0.0572)	-0.0674 (-0.078, -0.0569)
People like you can influence politics	-0.0388 (-0.0439, -0.0337)	-0.0813 (-0.0946, -0.068)	-0.085 (-0.0956, -0.0745)	-0.0854 (-0.0954, -0.0754)	-0.032 (-0.0465, -0.0175)	-0.0341 (-0.0475, -0.0207)	-0.0345 (-0.0479, -0.0212)	-0.0365 (-0.0499, -0.0232)
People like you have a say on what government does	-0.0385 (-0.0436, -0.0334)	-0.0809 (-0.0942, -0.0677)	-0.0854 (-0.0959, -0.0749)	-0.0863 (-0.0963, -0.0763)	-0.0373 (-0.0513, -0.0234)	-0.0391 (-0.052, -0.0262)	-0.0395 (-0.0524, -0.0265)	-0.0411 (-0.0539, -0.0282)
Perceived percentage of unemployed	-0.0391 (-0.0443, -0.0339)	-0.0807 (-0.0942, -0.0671)	-0.0853 (-0.0961, -0.0745)	-0.0898 (-0.1, -0.0795)	0.0301 (0.016, 0.0442)	0.0327 (0.0197, 0.0458)	0.0333 (0.0202, 0.0464)	0.0328 (0.0198, 0.0458)
Social benefits hurt business	-0.0389 (-0.0441, -0.0337)	-0.0898 (-0.1032, -0.0764)	-0.0989 (-0.1095, -0.0883)	-0.1014 (-0.1114, -0.0913)	-0.1165 (-0.1284, -0.1046)	-0.1151 (-0.1262, -0.104)	-0.1154 (-0.1265, -0.1044)	-0.1151 (-0.1262, -0.104)
Social benefits hurt country economy	-0.0387 (-0.0438, -0.0336)	-0.0888 (-0.1021, -0.0756)	-0.0951 (-0.1056, -0.0847)	-0.0976 (-0.1075, -0.0876)	-0.0894 (-0.1012, -0.0776)	-0.0881 (-0.0991, -0.0772)	-0.0885 (-0.0994, -0.0776)	-0.0883 (-0.0992, -0.0774)
Social benefits lead to equal society	-0.0395 (-0.0446, -0.0344)	-0.086 (-0.0992, -0.0728)	-0.0925 (-0.1028, -0.0822)	-0.0941 (-0.1039, -0.0843)	0.0708 (0.0583, 0.0833)	0.0773 (0.0658, 0.0889)	0.0774 (0.0658, 0.089)	0.0778 (0.0662, 0.0894)
Social benefits make people lazy	-0.0381 (-0.0432, -0.0331)	-0.0912 (-0.1043, -0.0782)	-0.1003 (-0.1105, -0.09)	-0.1011 (-0.1109, -0.0914)	-0.1074 (-0.1183, -0.0965)	-0.1095 (-0.1196, -0.0994)	-0.1095 (-0.1196, -0.0994)	-0.1099 (-0.12, -0.0999)
Social benefits make people less solidary	-0.0393 (-0.0444, -0.0342)	-0.0905 (-0.1037, -0.0773)	-0.0972 (-0.1076, -0.0869)	-0.1003 (-0.1102, -0.0904)	-0.0724 (-0.0839, -0.0609)	-0.0708 (-0.0814, -0.0602)	-0.0709 (-0.0815, -0.0602)	-0.0703 (-0.0809, -0.0597)
Social benefits prevent widespread poverty	-0.0399 (-0.045, -0.0347)	-0.0889 (-0.102, -0.0757)	-0.0943 (-0.1046, -0.084)	-0.0958 (-0.1056, -0.086)	0.0412 (0.0283, 0.0541)	0.0502 (0.0383, 0.0621)	0.0503 (0.0384, 0.0621)	0.0508 (0.0389, 0.0626)
State of the education	-0.0404 (-0.0457, -0.0351)	-0.0881 (-0.1017, -0.0745)	-0.0904 (-0.1011, -0.0798)	-0.0926 (-0.1028, -0.0825)	-0.0104 (-0.0172, -0.0036)	-0.0129 (-0.0191, -0.0066)	-0.013 (-0.0192, -0.0067)	-0.0134 (-0.0197, -0.0072)
State of the health services	-0.041 (-0.0463, -0.0358)	-0.0879 (-0.1014, -0.0744)	-0.0896 (-0.1002, -0.079)	-0.0923 (-0.1024, -0.0823)	-0.0211 (-0.0275, -0.0147)	-0.0232 (-0.0291, -0.0173)	-0.0234 (-0.0293, -0.0174)	-0.0235 (-0.0294, -0.0176)
Too few benefit to poor that are entitled	-0.0366 (-0.0419, -0.0313)	-0.0733 (-0.087, -0.0596)	-0.0759 (-0.0867, -0.0651)	-0.0787 (-0.0889, -0.0685)	0.1337 (0.1203, 0.1471)	0.139 (0.1266, 0.1514)	0.1393 (0.1269, 0.1517)	0.1401 (0.1277, 0.1524)
Too much benefits for many undeserving	-0.0405 (-0.0457, -0.0353)	-0.0885 (-0.102, -0.0751)	-0.0933 (-0.1039, -0.0827)	-0.0953 (-0.1054, -0.0852)	-0.0208 (-0.0336, -0.0081)	-0.0214 (-0.0332, -0.0096)	-0.0214 (-0.0332, -0.0097)	-0.0207 (-0.0324, -0.0089)
Unemployed standard of living is not bad	-0.0374 (-0.0425, -0.0324)	-0.0817 (-0.0948, -0.0687)	-0.09 (-0.1003, -0.0798)	-0.0891 (-0.0988, -0.0793)	-0.0696 (-0.076, -0.0631)	-0.0692 (-0.0751, -0.0633)	-0.0693 (-0.0751, -0.0634)	-0.0696 (-0.0754, -0.0637)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

Table C.12: Effect of socioeconomic position (SEP) ($\hat{\beta}_1$) and perception ($\hat{\beta}_2$) on welfare preference (Social benefits only for poor while middle and high income are take care of themselves) for varios measures of SEP and perception dimensions.

	Effect of SEP on preferences given perceptions ($\hat{\beta}_1$)				Effect of perceptions on preferences given SEP ($\hat{\beta}_2$)			
Perception	SEP-1	SEP-2	SEP-3	SEP-4	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	-0.0308 (-0.0374, -0.0241)	-0.0997 (-0.1168, -0.0827)	-0.117 (-0.1304, -0.1036)	-0.1397 (-0.1525, -0.1269)	0.0503 (0.0334, 0.0672)	0.0569 (0.0414, 0.0724)	0.0571 (0.0416, 0.0726)	0.0592 (0.0436, 0.0747)
Can take active role in political issues	-0.0314 (-0.038, -0.0247)	-0.0986 (-0.1159, -0.0813)	-0.1138 (-0.1276, -0.0999)	-0.1352 (-0.1485, -0.1219)	-0.0289 (-0.0453, -0.0125)	-0.0252 (-0.0403, -0.01)	-0.0251 (-0.0402, -0.0099)	-0.0313 (-0.0464, -0.0161)
Confident that can participate in politics	-0.031 (-0.0377, -0.0244)	-0.0964 (-0.1136, -0.0791)	-0.1116 (-0.1255, -0.0978)	-0.1342 (-0.1475, -0.1209)	-0.0364 (-0.0532, -0.0195)	-0.0361 (-0.0516, -0.0206)	-0.036 (-0.0515, -0.0205)	-0.0407 (-0.0562, -0.0252)
Country economy is doing well	-0.031 (-0.0377, -0.0243)	-0.1021 (-0.1192, -0.0849)	-0.1188 (-0.1323, -0.1053)	-0.1413 (-0.1543, -0.1284)	-0.0007 (-0.0085, 0.0071)	-0.0011 (-0.0083, 0.0061)	-0.0013 (-0.0084, 0.0059)	-0.0011 (-0.0082, 0.0061)
Government overall performance	-0.0304 (-0.0371, -0.0236)	-0.1009 (-0.1183, -0.0835)	-0.1186 (-0.1323, -0.105)	-0.1417 (-0.1548, -0.1287)	-0.0005 (-0.007, 0.0061)	-0.0015 (-0.0076, 0.0045)	-0.0016 (-0.0076, 0.0044)	-0.0016 (-0.0077, 0.0044)
Important strong government to ensure safety	-0.0322 (-0.0388, -0.0255)	-0.104 (-0.1211, -0.0869)	-0.1208 (-0.1342, -0.1073)	-0.1435 (-0.1563, -0.1306)	-0.0063 (-0.0197, 0.0071)	-0.0045 (-0.017, 0.0079)	-0.0044 (-0.0168, 0.008)	-0.0025 (-0.015, 0.0099)
Important to be modest	-0.0313 (-0.038, -0.0247)	-0.1012 (-0.1183, -0.0842)	-0.1185 (-0.132, -0.1051)	-0.1409 (-0.1537, -0.128)	0.016 (0.0024, 0.0296)	0.0217 (0.0091, 0.0342)	0.0218 (0.0093, 0.0344)	0.0248 (0.0123, 0.0374)
Important to be rich	-0.0322 (-0.0389, -0.0256)	-0.1037 (-0.1208, -0.0867)	-0.1212 (-0.1347, -0.1078)	-0.143 (-0.1558, -0.1301)	0.0078 (-0.004, 0.0196)	0.0063 (-0.0047, 0.0173)	0.0063 (-0.0046, 0.0173)	-0.0042 (-0.015, 0.0067)
Important to be successful	-0.0327 (-0.0394, -0.0261)	-0.1039 (-0.121, -0.0869)	-0.1212 (-0.1347, -0.1078)	-0.1426 (-0.1555, -0.1297)	0.0127 (0.0003, 0.0251)	0.0066 (-0.0049, 0.0181)	0.0067 (-0.0048, 0.0182)	-0.0042 (-0.0156, 0.0071)
Important to have equal opportunities and be treated equally	-0.0323 (-0.039, -0.0257)	-0.1041 (-0.1212, -0.087)	-0.1209 (-0.1343, -0.1075)	-0.1436 (-0.1563, -0.1308)	-0.0035 (-0.0188, 0.0118)	0.0017 (-0.0124, 0.0157)	0.0017 (-0.0123, 0.0158)	0.0005 (-0.0136, 0.0146)
Important to live in safe surroundings	-0.0322 (-0.0388, -0.0255)	-0.1029 (-0.12, -0.0859)	-0.1204 (-0.1338, -0.107)	-0.1425 (-0.1553, -0.1297)	-0.0018 (-0.015, 0.0115)	0.004 (-0.0083, 0.0163)	0.004 (-0.0083, 0.0164)	0.0075 (-0.0048, 0.0198)
Important to make autonomous decisions and be free	-0.0324 (-0.039, -0.0257)	-0.1039 (-0.1209, -0.0868)	-0.1206 (-0.1341, -0.1072)	-0.1432 (-0.156, -0.1304)	-0.0033 (-0.0182, 0.0116)	-0.0012 (-0.0148, 0.0125)	-0.0009 (-0.0145, 0.0128)	-0.0015 (-0.0152, 0.0121)
Large inequality is acceptable to reward effort	-0.0316 (-0.0383, -0.025)	-0.1018 (-0.1188, -0.0847)	-0.1189 (-0.1323, -0.1055)	-0.1416 (-0.1544, -0.1288)	-0.0131 (-0.0274, 0.0011)	-0.0237 (-0.0369, -0.0105)	-0.0238 (-0.037, -0.0106)	-0.0254 (-0.0386, -0.0122)
Likely to be unemployed soon	-0.0294 (-0.0368, -0.022)	-0.0992 (-0.1185, -0.0799)	-0.1145 (-0.1296, -0.0994)	-0.1329 (-0.1477, -0.1181)	0.0321 (0.0168, 0.0474)	0.0328 (0.0187, 0.0468)	0.033 (0.019, 0.0471)	0.0212 (0.0074, 0.035)
Most unemployed people do not try to find a job	-0.0327 (-0.0394, -0.0261)	-0.0988 (-0.116, -0.0817)	-0.1137 (-0.1273, -0.1001)	-0.1377 (-0.1506, -0.1247)	0.0543 (0.0394, 0.0692)	0.0473 (0.0336, 0.0611)	0.0474 (0.0336, 0.0611)	0.0455 (0.0318, 0.0593)
People like you can influence politics	-0.0316 (-0.0383, -0.025)	-0.102 (-0.1192, -0.0848)	-0.1184 (-0.1321, -0.1048)	-0.1407 (-0.1538, -0.1276)	-0.006 (-0.0248, 0.0129)	-0.0119 (-0.0293, 0.0055)	-0.0122 (-0.0296, 0.0052)	-0.0195 (-0.0369, -0.0021)
People like you have a say on what government does	-0.032 (-0.0387, -0.0254)	-0.1034 (-0.1206, -0.0862)	-0.1205 (-0.1342, -0.1069)	-0.1431 (-0.1561, -0.13)	0.004 (-0.0142, 0.0221)	0.002 (-0.0148, 0.0188)	0.0018 (-0.015, 0.0186)	-0.0021 (-0.0189, 0.0147)
Perceived percentage of unemployed	-0.03 (-0.0367, -0.0232)	-0.0986 (-0.1161, -0.081)	-0.1139 (-0.1279, -0.0999)	-0.1387 (-0.152, -0.1253)	0.0402 (0.0219, 0.0585)	0.0372 (0.0203, 0.0542)	0.0375 (0.0205, 0.0544)	0.0316 (0.0147, 0.0486)
Social benefits hurt business	-0.0327 (-0.0395, -0.026)	-0.1012 (-0.1186, -0.0838)	-0.1168 (-0.1306, -0.1031)	-0.1404 (-0.1535, -0.1272)	0.0492 (0.0337, 0.0646)	0.0432 (0.0288, 0.0576)	0.0429 (0.0285, 0.0573)	0.0435 (0.0291, 0.0579)
Social benefits hurt country economy	-0.0336 (-0.0402, -0.0269)	-0.1021 (-0.1193, -0.0849)	-0.1162 (-0.1298, -0.1026)	-0.1402 (-0.1532, -0.1273)	0.0654 (0.0502, 0.0807)	0.0616 (0.0474, 0.0757)	0.0612 (0.047, 0.0754)	0.0621 (0.0479, 0.0763)
Social benefits lead to equal society	-0.0324 (-0.039, -0.0257)	-0.1013 (-0.1184, -0.0842)	-0.119 (-0.1324, -0.1055)	-0.1421 (-0.155, -0.1292)	0.0285 (0.0123, 0.0447)	0.0248 (0.0098, 0.0399)	0.0248 (0.0098, 0.0399)	0.0247 (0.0096, 0.0397)
Social benefits make people lazy	-0.0328 (-0.0395, -0.0262)	-0.1014 (-0.1184, -0.0843)	-0.115 (-0.1285, -0.1015)	-0.1394 (-0.1523, -0.1266)	0.0496 (0.0353, 0.0638)	0.0398 (0.0266, 0.053)	0.0397 (0.0265, 0.0529)	0.0369 (0.0236, 0.0501)
Social benefits make people less solidary	-0.0327 (-0.0393, -0.026)	-0.0983 (-0.1155, -0.0812)	-0.1131 (-0.1266, -0.0995)	-0.1352 (-0.1482, -0.1223)	0.0773 (0.0624, 0.0922)	0.0695 (0.0557, 0.0834)	0.0695 (0.0556, 0.0833)	0.0721 (0.0582, 0.0859)
Social benefits prevent widespread poverty	-0.0325 (-0.0391, -0.0258)	-0.1034 (-0.1205, -0.0862)	-0.1203 (-0.1338, -0.1068)	-0.1423 (-0.1552, -0.1295)	0.0305 (0.0138, 0.0473)	0.0262 (0.0108, 0.0416)	0.0262 (0.0108, 0.0416)	0.0289 (0.0135, 0.0444)
State of the education	-0.032 (-0.0388, -0.0252)	-0.1077 (-0.1253, -0.0901)	-0.12 (-0.1338, -0.1062)	-0.142 (-0.1552, -0.1288)	0.0049 (-0.0039, 0.0136)	0.0044 (-0.0037, 0.0126)	0.0043 (-0.0038, 0.0124)	0.0028 (-0.0053, 0.011)
State of the health services	-0.0295 (-0.0363, -0.0227)	-0.1009 (-0.1185, -0.0834)	-0.1176 (-0.1314, -0.1038)	-0.1399 (-0.1531, -0.1267)	-0.0053 (-0.0137, 0.0031)	-0.0047 (-0.0124, 0.0031)	-0.0047 (-0.0125, 0.003)	-0.0045 (-0.0122, 0.0033)
Too few benefit to poor that are entitled	-0.0287 (-0.0356, -0.0218)	-0.0965 (-0.1143, -0.0787)	-0.1149 (-0.129, -0.1008)	-0.1389 (-0.1523, -0.1255)	0.0786 (0.0611, 0.0961)	0.0816 (0.0655, 0.0978)	0.0817 (0.0656, 0.0979)	0.0817 (0.0655, 0.0979)
Too much benefits for many undeserving	-0.0315 (-0.0382, -0.0248)	-0.1021 (-0.1194, -0.0847)	-0.1191 (-0.1329, -0.1054)	-0.1427 (-0.1558, -0.1296)	0.0342 (0.0178, 0.0507)	0.0246 (0.0093, 0.0398)	0.0246 (0.0094, 0.0398)	0.0271 (0.0118, 0.0423)
Unemployed standard of living is not bad	-0.031 (-0.0376, -0.0243)	-0.1034 (-0.1205, -0.0862)	-0.1207 (-0.1341, -0.1072)	-0.1411 (-0.154, -0.1283)	-0.0304 (-0.0388, -0.0219)	-0.0322 (-0.0399, -0.0245)	-0.0322 (-0.0399, -0.0245)	-0.0357 (-0.0434, -0.028)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

Table C.13: Effect of socioeconomic position (SEP) ($\hat{\beta}_1$) and perception ($\hat{\beta}_2$) on welfare preference (Spend more in training program for unemployed and less in unemployment benefits) for varios measures of SEP and perception dimensions.

	Effect of SEP on preferences given perceptions ($\hat{\beta}_1$)				Effect of perceptions on preferences given SEP ($\hat{\beta}_2$)			
Perception	SEP-1	SEP-2	SEP-3	SEP-4	SEP-1	SEP-2	SEP-3	SEP-4
A society to be fair, inequality needs to be low	0.0203 (0.014, 0.0265)	0.03 (0.0139, 0.0461)	0.0345 (0.0218, 0.0472)	0.039 (0.0269, 0.0512)	-0.0659 (-0.0819, -0.0499)	-0.0605 (-0.0753, -0.0458)	-0.0606 (-0.0754, -0.0459)	-0.0616 (-0.0763, -0.0469)
Can take active role in political issues	0.0227 (0.0164, 0.0289)	0.0362 (0.0198, 0.0526)	0.0399 (0.0268, 0.053)	0.0444 (0.0318, 0.057)	-0.005 (-0.0204, 0.0105)	-0.0039 (-0.0182, 0.0104)	-0.0038 (-0.0181, 0.0105)	-0.0009 (-0.0152, 0.0134)
Confident that can participate in politics	0.0224 (0.0161, 0.0287)	0.0364 (0.0201, 0.0528)	0.0411 (0.028, 0.0542)	0.0452 (0.0326, 0.0577)	-0.0101 (-0.026, 0.0059)	-0.0062 (-0.0208, 0.0085)	-0.0061 (-0.0208, 0.0085)	-0.0036 (-0.0183, 0.011)
Country economy is doing well	0.0181 (0.0118, 0.0244)	0.0232 (0.007, 0.0394)	0.0288 (0.016, 0.0416)	0.0336 (0.0214, 0.0458)	0.0432 (0.0358, 0.0505)	0.0437 (0.0369, 0.0505)	0.0437 (0.037, 0.0505)	0.044 (0.0373, 0.0508)
Government overall performance	0.0211 (0.0147, 0.0275)	0.0326 (0.0162, 0.0491)	0.037 (0.024, 0.05)	0.0428 (0.0305, 0.0552)	0.022 (0.0157, 0.0282)	0.0213 (0.0156, 0.027)	0.0214 (0.0156, 0.0271)	0.0215 (0.0158, 0.0272)
Important strong government to ensure safety	0.0222 (0.0159, 0.0285)	0.0357 (0.0195, 0.0518)	0.041 (0.0283, 0.0538)	0.0461 (0.0339, 0.0582)	0.0125 (-0.0002, 0.0252)	0.0177 (0.0059, 0.0295)	0.0176 (0.0059, 0.0294)	0.0173 (0.0056, 0.0291)
Important to be modest	0.0226 (0.0163, 0.0288)	0.0361 (0.0199, 0.0522)	0.041 (0.0283, 0.0538)	0.0464 (0.0343, 0.0585)	0.0175 (0.0046, 0.0303)	0.0244 (0.0125, 0.0363)	0.0243 (0.0124, 0.0362)	0.0237 (0.0118, 0.0355)
Important to be rich	0.022 (0.0157, 0.0283)	0.0334 (0.0172, 0.0495)	0.0384 (0.0257, 0.0511)	0.0414 (0.0292, 0.0535)	0.0244 (0.0133, 0.0356)	0.0228 (0.0124, 0.0331)	0.0228 (0.0124, 0.0331)	0.0251 (0.0149, 0.0353)
Important to be successful	0.0211 (0.0148, 0.0274)	0.0312 (0.015, 0.0473)	0.0358 (0.0231, 0.0486)	0.0384 (0.0262, 0.0506)	0.0332 (0.0215, 0.0449)	0.0327 (0.0219, 0.0436)	0.0327 (0.0219, 0.0436)	0.0348 (0.0241, 0.0455)
Important to have equal opportunities and be treated equally	0.0221 (0.0158, 0.0284)	0.0341 (0.018, 0.0503)	0.0391 (0.0264, 0.0518)	0.0438 (0.0317, 0.0559)	-0.0101 (-0.0246, 0.0043)	-0.0036 (-0.0169, 0.0098)	-0.0036 (-0.0169, 0.0097)	-0.0027 (-0.0161, 0.0106)
Important to live in safe surroundings	0.0221 (0.0159, 0.0284)	0.0344 (0.0183, 0.0506)	0.0389 (0.0262, 0.0516)	0.0438 (0.0317, 0.0559)	0.0016 (-0.0109, 0.0141)	0.0011 (-0.0106, 0.0127)	0.001 (-0.0106, 0.0127)	-0.0002 (-0.0118, 0.0114)
Important to make autonomous decisions and be free	0.0223 (0.0161, 0.0286)	0.0331 (0.0169, 0.0492)	0.0381 (0.0254, 0.0508)	0.043 (0.0309, 0.0552)	0.02 (0.006, 0.0341)	0.0215 (0.0086, 0.0345)	0.0215 (0.0085, 0.0344)	0.0214 (0.0085, 0.0344)
Large inequality is acceptable to reward effort	0.0193 (0.013, 0.0255)	0.0295 (0.0134, 0.0456)	0.0347 (0.022, 0.0473)	0.0401 (0.028, 0.0522)	0.095 (0.0816, 0.1084)	0.0886 (0.0762, 0.1011)	0.0887 (0.0763, 0.1011)	0.0893 (0.0769, 0.1017)
Likely to be unemployed soon	0.0206 (0.0137, 0.0276)	0.039 (0.0208, 0.0572)	0.0434 (0.0291, 0.0577)	0.0535 (0.0395, 0.0675)	-0.0508 (-0.0652, -0.0364)	-0.0544 (-0.0677, -0.0411)	-0.0545 (-0.0678, -0.0412)	-0.0479 (-0.0609, -0.0348)
Most unemployed people do not try to find a job	0.0225 (0.0163, 0.0288)	0.0525 (0.0364, 0.0685)	0.0643 (0.0515, 0.0771)	0.068 (0.0559, 0.0802)	0.1569 (0.1429, 0.171)	0.158 (0.1451, 0.1709)	0.1578 (0.1449, 0.1708)	0.158 (0.1451, 0.1709)
People like you can influence politics	0.0208 (0.0145, 0.0271)	0.0266 (0.0103, 0.0428)	0.0298 (0.0168, 0.0427)	0.0331 (0.0208, 0.0455)	0.0669 (0.0491, 0.0847)	0.068 (0.0516, 0.0845)	0.0682 (0.0518, 0.0847)	0.0707 (0.0543, 0.0871)
People like you have a say on what government does	0.0208 (0.0146, 0.0271)	0.0258 (0.0096, 0.042)	0.0288 (0.0159, 0.0417)	0.0331 (0.0208, 0.0454)	0.0749 (0.0578, 0.092)	0.0779 (0.062, 0.0938)	0.078 (0.0621, 0.0939)	0.0793 (0.0635, 0.0952)
Perceived percentage of unemployed	0.021 (0.0146, 0.0273)	0.0306 (0.014, 0.0472)	0.0369 (0.0236, 0.0502)	0.0426 (0.03, 0.0552)	-0.0046 (-0.0219, 0.0128)	-0.009 (-0.0251, 0.007)	-0.0091 (-0.0252, 0.0069)	-0.0074 (-0.0234, 0.0085)
Social benefits hurt business	0.0214 (0.0151, 0.0277)	0.0366 (0.0202, 0.0529)	0.0459 (0.0329, 0.0588)	0.0514 (0.0391, 0.0638)	0.1091 (0.0946, 0.1237)	0.1108 (0.0973, 0.1244)	0.1108 (0.0973, 0.1243)	0.1103 (0.0967, 0.1238)
Social benefits hurt country economy	0.0194 (0.0131, 0.0257)	0.0344 (0.0183, 0.0506)	0.0441 (0.0313, 0.0569)	0.0487 (0.0365, 0.0608)	0.1135 (0.0992, 0.1279)	0.1127 (0.0994, 0.1261)	0.1127 (0.0994, 0.1261)	0.1123 (0.0989, 0.1256)
Social benefits lead to equal society	0.0226 (0.0163, 0.0289)	0.0355 (0.0193, 0.0517)	0.04 (0.0273, 0.0528)	0.0455 (0.0333, 0.0576)	0.0318 (0.0164, 0.0472)	0.0313 (0.0171, 0.0456)	0.0313 (0.0171, 0.0456)	0.0312 (0.017, 0.0455)
Social benefits make people lazy	0.0199 (0.0137, 0.0261)	0.0421 (0.0261, 0.0581)	0.0523 (0.0397, 0.0649)	0.0562 (0.0442, 0.0682)	0.1566 (0.1432, 0.17)	0.1532 (0.1408, 0.1655)	0.1531 (0.1407, 0.1655)	0.1534 (0.141, 0.1657)
Social benefits make people less solidary	0.0209 (0.0147, 0.0271)	0.0429 (0.0268, 0.0589)	0.0529 (0.0402, 0.0656)	0.0597 (0.0475, 0.0718)	0.1491 (0.1351, 0.1632)	0.1503 (0.1373, 0.1632)	0.1502 (0.1373, 0.1632)	0.1488 (0.1358, 0.1618)
Social benefits prevent widespread poverty	0.0223 (0.016, 0.0286)	0.0334 (0.0173, 0.0496)	0.0381 (0.0254, 0.0509)	0.0439 (0.0317, 0.056)	0.0321 (0.0162, 0.048)	0.0247 (0.01, 0.0393)	0.0247 (0.01, 0.0393)	0.0237 (0.0091, 0.0383)
State of the education	0.0211 (0.0147, 0.0276)	0.0328 (0.0162, 0.0494)	0.0386 (0.0255, 0.0517)	0.0428 (0.0303, 0.0553)	0.0253 (0.017, 0.0336)	0.0239 (0.0162, 0.0316)	0.024 (0.0163, 0.0316)	0.0242 (0.0166, 0.0319)
State of the health services	0.0213 (0.0148, 0.0277)	0.0331 (0.0166, 0.0497)	0.0375 (0.0244, 0.0506)	0.0428 (0.0303, 0.0552)	0.0195 (0.0116, 0.0274)	0.0205 (0.0131, 0.0278)	0.0205 (0.0132, 0.0278)	0.0208 (0.0135, 0.0281)
Too few benefit to poor that are entitled	0.0221 (0.0156, 0.0286)	0.0316 (0.0147, 0.0484)	0.0373 (0.0239, 0.0506)	0.0424 (0.0297, 0.0551)	-0.051 (-0.0675, -0.0344)	-0.0541 (-0.0694, -0.0388)	-0.0542 (-0.0695, -0.0389)	-0.0547 (-0.07, -0.0394)
Too much benefits for many undeserving	0.0222 (0.0159, 0.0286)	0.0403 (0.024, 0.0567)	0.0499 (0.037, 0.0628)	0.0557 (0.0434, 0.068)	0.1064 (0.0909, 0.1219)	0.1027 (0.0884, 0.1171)	0.1026 (0.0882, 0.1169)	0.1019 (0.0876, 0.1163)
Unemployed standard of living is not bad	0.0212 (0.0149, 0.0275)	0.0332 (0.017, 0.0494)	0.0387 (0.026, 0.0515)	0.0415 (0.0294, 0.0536)	0.0523 (0.0444, 0.0603)	0.0518 (0.0445, 0.0591)	0.0518 (0.0445, 0.0591)	0.0527 (0.0454, 0.06)

Note:
Controls: Education (years), ISEI08, age, our, gender, unemployed, union, religion
[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

C.2.4 Propotion of the effect of SEP that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$

The Table C.14 shows the proportion of the effect of SEP on policy attitudes that goes through perceptions for various measures of SEP, perceptions, and policy attitudes. It is ordered by the column "SEP-3". Consider the first row. The proportion of the effect of SEP on the preferences about the government should "ensure living standard for unemployed" (second column) that goes through the effect of income on the perception that "Most unemployed people do not try to find a job" (first column), is only 2% if only income is considered as measure of SEP (third column). It is 56% if income is combined with education, and it reaches 132% if income is combined with education and ISEI-08. In the main paper, we used as example SEP measured using income only, perception measured as "A society to be fair, inequality needs to be low", and the attitude about government responsibility to "Reduce income differences". As in the main paper, the Table C.14 shows that the proportion of the effect of SEP on preferences that goes through perceptions is 28% if income alone is considered, 29% is we use income and education to construct SEP, 25% if ISEI-08 is also used, and 28% if age is also include to construct the SEP index. The Table C.14 shows the sensitivity of our conclusions due to the construction of SEP. As we can see, for many combinations the conclusions does not change substantially, but in some cases some dimensions of the SEP seem to be more important. The section C.2.5 below summarizes all the results presented in the Table C.14.

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes.

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Most unemployed people do not try to find a job	Ensure living standard for unemployed	0.0242	0.5636	1.3239	0.8336
Social benefits make people lazy	Ensure living standard for unemployed	0.1077	0.2912	0.8013	0.4761
Most unemployed people do not try to find a job	Spend more in training program for unemployed and less in unemployment benefits	0.0198	0.5098	0.6178	0.5112
Social benefits make people less solidary	Ensure living standard for unemployed	0.0314	0.2470	0.6029	0.4426
Too much benefits for many undeserving	Ensure living standard for unemployed	0.0278	0.1899	0.5135	0.3640

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
A society to be fair, inequality needs to be low	Ensure living standard for unemployed	0.2103	0.2782	0.4406	0.3416
Social benefits hurt business	Ensure living standard for unemployed	0.0627	0.1145	0.4295	0.2822
Most unemployed people do not try to find a job	Ensure basic income for all	0.0073	0.1916	0.3856	1.0001
Too few benefit to poor that are entitled	Ensure living standard for unemployed	0.0977	0.1892	0.3537	0.2233
Social benefits make people lazy	Spend more in training program for unemployed and less in unemployment benefits	0.0838	0.2442	0.3468	0.2709
Social benefits make people less solidary	Spend more in training program for unemployed and less in unemployment benefits	0.0302	0.2655	0.3344	0.3217
A society to be fair, inequality needs to be low	Ensure basic income for all	0.1549	0.2176	0.2954	0.9588
Social benefits make people lazy	Ensure basic income for all	0.0403	0.1224	0.2886	0.7102
Perceived percentage of unemployed	Ensure living standard for unemployed	0.0450	0.1502	0.2855	0.1482
People like you have a say on what government does	Spend more in training program for unemployed and less in unemployment benefits	0.0914	0.2674	0.2755	0.2567
Country economy is doing well	Spend more in training program for unemployed and less in unemployment benefits	0.1782	0.3181	0.2706	0.2285
Too much benefits for many undeserving	Ensure basic income for all	0.0134	0.1161	0.2691	0.8247
People like you can influence politics	Spend more in training program for unemployed and less in unemployment benefits	0.0805	0.2585	0.2675	0.2658
Too few benefit to poor that are entitled	Ensure basic income for all	0.0789	0.1623	0.2609	0.7111
A society to be fair, inequality needs to be low	Reduce income differences	0.2874	0.2911	0.2557	0.2897
Social benefits hurt country economy	Ensure living standard for unemployed	0.1230	0.0246	0.2549	0.1615
Too much benefits for many undeserving	Spend more in training program for unemployed and less in unemployment benefits	0.0235	0.1816	0.2526	0.2354
People like you can influence politics	Ensure standard of living for the old	0.1359	0.2260	0.2305	0.2350
Large inequality is acceptable to reward effort	Ensure living standard for unemployed	0.1539	0.1440	0.2204	0.1529

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
People like you can influence politics	Ensure basic income for all	0.0348	0.1200	0.2030	0.6737
Social benefits hurt business	Spend more in training program for unemployed and less in unemployment benefits	0.0499	0.1026	0.1983	0.1710
People like you have a say on what government does	Ensure standard of living for the old	0.1275	0.1927	0.1957	0.1922
Perceived percentage of unemployed	Ensure standard of living for the old	0.1487	0.2042	0.1951	0.1587
Likely to be unemployed soon	Ensure living standard for unemployed	0.0981	0.1130	0.1897	0.0336
Social benefits hurt business	Ensure basic income for all	0.0273	0.0583	0.1876	0.5243
Social benefits make people less solidary	Ensure basic income for all	0.0098	0.0851	0.1782	0.5701
People like you have a say on what government does	Ensure basic income for all	0.0324	0.0991	0.1675	0.5099
Too few benefit to poor that are entitled	Reduce income differences	0.1070	0.1572	0.1632	0.1522
Important strong government to ensure safety	Ensure living standard for unemployed	0.0121	0.0660	0.1595	0.1230
Too few benefit to poor that are entitled	Spend more in training program for unemployed and less in unemployment benefits	0.0724	0.1533	0.1480	0.1246
Too few benefit to poor that are entitled	Ensure standard of living for the old	0.1588	0.1543	0.1469	0.1321
Likely to be unemployed soon	Spend more in training program for unemployed and less in unemployment benefits	0.1430	0.1697	0.1464	0.0345
Country economy is doing well	Ensure standard of living for the old	0.1912	0.1736	0.1458	0.1314
A society to be fair, inequality needs to be low	Ensure standard of living for the old	0.2453	0.1778	0.1432	0.1562
Country economy is doing well	Ensure living standard for unemployed	0.0412	0.0828	0.1393	0.0863
Important strong government to ensure safety	Ensure standard of living for the old	0.0391	0.1106	0.1368	0.1493
Confident that can participate in politics	Ensure basic income for all	0.0131	0.0771	0.1349	0.4375
Country economy is doing well	Reduce income differences	0.1119	0.1415	0.1299	0.1220
Large inequality is acceptable to reward effort	Reduce income differences	0.2044	0.1501	0.1274	0.1296
Social benefits prevent widespread poverty	Ensure living standard for unemployed	0.0025	0.0467	0.1243	0.0450
Unemployed standard of living is not bad	Ensure living standard for unemployed	0.1137	0.1435	0.1208	0.2078

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Social benefits hurt country economy	Spend more in training program for unemployed and less in unemployment benefits	0.1025	0.0222	0.1184	0.0985
Likely to be unemployed soon	Ensure basic income for all	0.0592	0.0787	0.1139	0.1219
Most unemployed people do not try to find a job	Reduce income differences	0.0049	0.0875	0.1138	0.1041
Large inequality is acceptable to reward effort	Spend more in training program for unemployed and less in unemployment benefits	0.1400	0.1355	0.1070	0.0984
Social benefits make people lazy	Reduce income differences	0.0324	0.0697	0.1064	0.0927
Important to have equal opportunities and be treated equally	Ensure living standard for unemployed	0.0446	0.0266	0.1063	0.0897
Large inequality is acceptable to reward effort	Ensure basic income for all	0.0713	0.0806	0.1059	0.3097
Important to be modest	Ensure living standard for unemployed	0.0229	0.0556	0.1030	0.0882
Social benefits hurt country economy	Ensure basic income for all	0.0491	0.0115	0.1021	0.2755
Can take active role in political issues	Ensure basic income for all	0.0111	0.0603	0.1018	0.3682
A society to be fair, inequality needs to be low	Spend more in training program for unemployed and less in unemployment benefits	0.0890	0.1156	0.0946	0.0978
Most unemployed people do not try to find a job	Ensure standard of living for the old	0.0053	0.0747	0.0888	0.0805
Social benefits hurt business	Reduce income differences	0.0300	0.0426	0.0886	0.0852
Social benefits make people lazy	Ensure standard of living for the old	0.0412	0.0617	0.0861	0.0729
Government overall performance	Spend more in training program for unemployed and less in unemployment benefits	0.0472	0.1015	0.0843	0.0642
Social benefits hurt business	Ensure standard of living for the old	0.0438	0.0442	0.0842	0.0786
Social benefits lead to equal society	Ensure living standard for unemployed	0.0080	0.0083	0.0794	0.0289
Perceived percentage of unemployed	Ensure basic income for all	0.0161	0.0448	0.0768	0.2861
Can take active role in political issues	Ensure living standard for unemployed	0.0162	0.0383	0.0762	0.0423
Social benefits make people less solidary	Ensure standard of living for the old	0.0137	0.0610	0.0757	0.0803
People like you have a say on what government does	Ensure living standard for unemployed	0.0275	0.0379	0.0745	0.0457

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Important to be successful	Spend more in training program for unemployed and less in unemployment benefits	0.0391	0.0775	0.0726	0.1296
Too few benefit to poor that are entitled	Social benefits only for poor while middle and high income are take care of themselves	0.0776	0.0757	0.0715	0.0567
Perceived percentage of unemployed	Reduce income differences	0.0355	0.0675	0.0711	0.0593
Government overall performance	Ensure standard of living for the old	0.0760	0.0850	0.0695	0.0569
Social benefits prevent widespread poverty	Ensure basic income for all	0.0017	0.0299	0.0683	0.0986
Can take active role in political issues	Ensure standard of living for the old	0.0259	0.0651	0.0680	0.0656
Important to live in safe surroundings	Ensure standard of living for the old	0.0047	0.0512	0.0678	0.0797
Social benefits make people less solidary	Reduce income differences	0.0083	0.0499	0.0677	0.0725
People like you can influence politics	Ensure living standard for unemployed	0.0224	0.0342	0.0670	0.0376
Confident that can participate in politics	Social benefits only for poor while middle and high income are take care of themselves	0.0261	0.0612	0.0639	0.0643
People like you have a say on what government does	Reduce income differences	0.0257	0.0536	0.0597	0.0634
Perceived percentage of unemployed	Social benefits only for poor while middle and high income are take care of themselves	0.0584	0.0629	0.0597	0.0365
Most unemployed people do not try to find a job	Social benefits only for poor while middle and high income are take care of themselves	0.0048	0.0500	0.0594	0.0449
Important to make autonomous decisions and be free	Ensure standard of living for the old	0.0341	0.0494	0.0590	0.0630
People like you can influence politics	Reduce income differences	0.0217	0.0517	0.0581	0.0656
Social benefits hurt country economy	Ensure standard of living for the old	0.0960	0.0107	0.0561	0.0504
Too much benefits for many undeserving	Ensure standard of living for the old	0.0087	0.0404	0.0555	0.0555
Important to live in safe surroundings	Ensure living standard for unemployed	0.0008	0.0212	0.0545	0.0474
Large inequality is acceptable to reward effort	Ensure standard of living for the old	0.1330	0.0670	0.0521	0.0512

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Important to be modest	Ensure standard of living for the old	0.0493	0.0545	0.0513	0.0607
Important to make autonomous decisions and be free	Ensure living standard for unemployed	0.0040	0.0217	0.0512	0.0373
Confident that can participate in politics	Ensure living standard for unemployed	0.0090	0.0245	0.0508	0.0269
Social benefits make people less solidary	Social benefits only for poor while middle and high income are take care of themselves	0.0109	0.0402	0.0495	0.0475
Important to be successful	Ensure basic income for all	0.0153	0.0318	0.0489	0.3709
Important to have equal opportunities and be treated equally	Ensure basic income for all	0.0213	0.0138	0.0473	0.1728
Social benefits lead to equal society	Ensure basic income for all	0.0051	0.0058	0.0472	0.0722
Can take active role in political issues	Social benefits only for poor while middle and high income are take care of themselves	0.0239	0.0460	0.0469	0.0533
Perceived percentage of unemployed	Spend more in training program for unemployed and less in unemployment benefits	0.0095	0.0465	0.0455	0.0280
Likely to be unemployed soon	Reduce income differences	0.0505	0.0468	0.0437	0.0125
Confident that can participate in politics	Ensure standard of living for the old	0.0160	0.0396	0.0425	0.0383
State of the health services	Spend more in training program for unemployed and less in unemployment benefits	0.0217	0.0500	0.0423	0.0303
Important to be modest	Reduce income differences	0.0262	0.0411	0.0423	0.0524
Unemployed standard of living is not bad	Spend more in training program for unemployed and less in unemployment benefits	0.0697	0.0959	0.0416	0.0956
Government overall performance	Reduce income differences	0.0268	0.0461	0.0413	0.0350
Important to be modest	Spend more in training program for unemployed and less in unemployment benefits	0.0158	0.0433	0.0412	0.0444
Social benefits hurt country economy	Reduce income differences	0.0455	0.0069	0.0399	0.0370
Important to have equal opportunities and be treated equally	Ensure standard of living for the old	0.0576	0.0191	0.0388	0.0468
State of the health services	Ensure living standard for unemployed	0.0091	0.0220	0.0355	0.0193

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Important strong government to ensure safety	Spend more in training program for unemployed and less in unemployment benefits	0.0036	0.0283	0.0353	0.0353
Important strong government to ensure safety	Reduce income differences	0.0065	0.0258	0.0348	0.0394
Government overall performance	Ensure basic income for all	0.0075	0.0258	0.0346	0.0811
Unemployed standard of living is not bad	Ensure basic income for all	0.0351	0.0476	0.0345	0.2300
Important to live in safe surroundings	Ensure basic income for all	0.0008	0.0153	0.0343	0.1365
Confident that can participate in politics	Spend more in training program for unemployed and less in unemployment benefits	0.0104	0.0319	0.0340	0.0187
Important to have equal opportunities and be treated equally	Reduce income differences	0.0324	0.0146	0.0324	0.0403
Important to make autonomous decisions and be free	Spend more in training program for unemployed and less in unemployment benefits	0.0106	0.0261	0.0315	0.0310
Important to be successful	Reduce income differences	0.0239	0.0312	0.0315	0.0596
Social benefits make people lazy	Social benefits only for poor while middle and high income are take care of themselves	0.0184	0.0207	0.0288	0.0198
A society to be fair, inequality needs to be low	Social benefits only for poor while middle and high income are take care of themselves	0.0472	0.0355	0.0285	0.0286
Likely to be unemployed soon	Social benefits only for poor while middle and high income are take care of themselves	0.0628	0.0335	0.0284	0.0047
Important to be rich	Ensure basic income for all	0.0077	0.0256	0.0268	0.3625
Social benefits hurt business	Social benefits only for poor while middle and high income are take care of themselves	0.0156	0.0131	0.0246	0.0206
Important to be successful	Ensure living standard for unemployed	0.0038	0.0138	0.0243	0.0094
Social benefits prevent widespread poverty	Spend more in training program for unemployed and less in unemployment benefits	0.0012	0.0175	0.0240	0.0109
Government overall performance	Ensure living standard for unemployed	0.0110	0.0156	0.0240	0.0144
Unemployed standard of living is not bad	Reduce income differences	0.0522	0.0512	0.0239	0.0602

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Too much benefits for many undeserving	Reduce income differences	0.0026	0.0151	0.0226	0.0228
Can take active role in political issues	Spend more in training program for unemployed and less in unemployment benefits	0.0059	0.0217	0.0221	0.0051
Social benefits prevent widespread poverty	Reduce income differences	0.0009	0.0142	0.0210	0.0111
State of the health services	Reduce income differences	0.0132	0.0226	0.0206	0.0164
Social benefits hurt country economy	Social benefits only for poor while middle and high income are take care of themselves	0.0411	0.0040	0.0206	0.0166
Unemployed standard of living is not bad	Ensure standard of living for the old	0.0692	0.0481	0.0206	0.0490
State of the health services	Ensure standard of living for the old	0.0235	0.0245	0.0205	0.0159
Important strong government to ensure safety	Ensure basic income for all	0.0017	0.0097	0.0203	0.0755
Too much benefits for many undeserving	Social benefits only for poor while middle and high income are take care of themselves	0.0053	0.0142	0.0194	0.0190
Important to be rich	Ensure living standard for unemployed	0.0045	0.0156	0.0189	0.0357
Social benefits prevent widespread poverty	Ensure standard of living for the old	0.0011	0.0140	0.0189	0.0094
Confident that can participate in politics	Reduce income differences	0.0075	0.0148	0.0175	0.0211
Important to live in safe surroundings	Reduce income differences	0.0007	0.0118	0.0170	0.0215
Important to be rich	Spend more in training program for unemployed and less in unemployment benefits	0.0083	0.0246	0.0156	0.0600
People like you can influence politics	Social benefits only for poor while middle and high income are take care of themselves	0.0050	0.0148	0.0153	0.0224
Social benefits lead to equal society	Reduce income differences	0.0030	0.0027	0.0141	0.0075
Important to make autonomous decisions and be free	Reduce income differences	0.0026	0.0107	0.0140	0.0151
Social benefits lead to equal society	Spend more in training program for unemployed and less in unemployment benefits	0.0024	0.0027	0.0133	0.0063

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
Important to be modest	Social benefits only for poor while middle and high income are take care of themselves	0.0100	0.0126	0.0119	0.0142
Can take active role in political issues	Reduce income differences	0.0008	0.0102	0.0109	0.0065
Large inequality is acceptable to reward effort	Social benefits only for poor while middle and high income are take care of themselves	0.0134	0.0119	0.0092	0.0085
Important to be successful	Ensure standard of living for the old	0.0001	0.0097	0.0089	0.0193
Important to make autonomous decisions and be free	Ensure basic income for all	0.0019	0.0044	0.0086	0.0280
Unemployed standard of living is not bad	Social benefits only for poor while middle and high income are take care of themselves	0.0281	0.0195	0.0083	0.0198
Social benefits prevent widespread poverty	Social benefits only for poor while middle and high income are take care of themselves	0.0008	0.0061	0.0082	0.0040
Important to be rich	Ensure standard of living for the old	0.0056	0.0122	0.0076	0.0295
Social benefits lead to equal society	Ensure standard of living for the old	0.0026	0.0015	0.0073	0.0037
Likely to be unemployed soon	Ensure standard of living for the old	0.0104	0.0080	0.0070	0.0028
Country economy is doing well	Ensure basic income for all	0.0100	0.0023	0.0061	0.0257
Important to be successful	Social benefits only for poor while middle and high income are take care of themselves	0.0104	0.0052	0.0048	0.0048
State of the health services	Ensure basic income for all	0.0050	0.0022	0.0034	0.0093
Social benefits lead to equal society	Social benefits only for poor while middle and high income are take care of themselves	0.0015	0.0007	0.0034	0.0015
State of the health services	Social benefits only for poor while middle and high income are take care of themselves	0.0041	0.0037	0.0031	0.0020
Important strong government to ensure safety	Social benefits only for poor while middle and high income are take care of themselves	0.0013	0.0024	0.0028	0.0016
Country economy is doing well	Social benefits only for poor while middle and high income are take care of themselves	0.0020	0.0026	0.0025	0.0017
State of the education	Ensure living standard for unemployed	0.0135	0.0042	0.0023	0.0065

Table C.14: Proportion of the total effect of socioeconomic position (SEP) that goes through perceptions $\left(\left|\frac{\hat{\alpha}_1\hat{\beta}_2}{\hat{\lambda}_1}\right|\right)$ for various measures of SEP, perception, and policy attitudes. *(continued)*

Perception	Policy attitude	SEP-1[1]	SEP-2[2]	SEP-3[3]	SEP-4[4]
State of the education	Spend more in training program for unemployed and less in unemployment benefits	0.0258	0.0080	0.0023	0.0091
Important to live in safe surroundings	Social benefits only for poor while middle and high income are take care of themselves	0.0001	0.0016	0.0022	0.0043
People like you have a say on what government does	Social benefits only for poor while middle and high income are take care of themselves	0.0034	0.0023	0.0020	0.0021
Government overall performance	Social benefits only for poor while middle and high income are take care of themselves	0.0007	0.0024	0.0020	0.0015
Important to be rich	Reduce income differences	0.0021	0.0029	0.0020	0.0090
Important to have equal opportunities and be treated equally	Spend more in training program for unemployed and less in unemployment benefits	0.0041	0.0009	0.0019	0.0016
Important to live in safe surroundings	Spend more in training program for unemployed and less in unemployment benefits	0.0001	0.0013	0.0017	0.0004
Important to be modest	Ensure basic income for all	0.0031	0.0008	0.0016	0.0076
Important to be rich	Social benefits only for poor while middle and high income are take care of themselves	0.0019	0.0022	0.0014	0.0030
State of the education	Ensure basic income for all	0.0018	0.0014	0.0007	0.0099
State of the education	Reduce income differences	0.0060	0.0017	0.0005	0.0024
Important to make autonomous decisions and be free	Social benefits only for poor while middle and high income are take care of themselves	0.0012	0.0005	0.0004	0.0007
Important to have equal opportunities and be treated equally	Social benefits only for poor while middle and high income are take care of themselves	0.0010	0.0001	0.0003	0.0001
State of the education	Social benefits only for poor while middle and high income are take care of themselves	0.0034	0.0005	0.0001	0.0003
State of the education	Ensure standard of living for the old	0.0011	0.0001	0.0000	0.0001

[1] SEP-1: SEP using income only
[2] SEP-2: education added to SEP-1 index
[3] SEP-3: ISEI added to SEP-2 index
[4] SEP-4: age added to SEP-3 index

C.2.5 Summary of the effect of SEP that goes through perceptions

The Figures C.14 to C.16 reproduces the corresponding Figure in the main paper, but varying the way we measure SEP. We can see that depending on how we measure that variable, the proportion of its effect on preferences that goes through perceptions varies. Consider the Figure C.14, in which the SEP is captured by income only. The two perceptions that appears as the most important to explain the effect of SEP (income) on preferences ("Government should take measures to reduce differences in income levels") are "A society to be fair, inequality needs to be low" and "Large inequality is acceptable to reward effort", followed by the perceptions that "Country economy is doing well". As SEP (income) increases, people perceive that inequality is justifiable, is not related to fairness, and that the economy of the country is going well. The more they accept inequality, the less they support policies to reduce differences in income levels (middle panel in the Figure C.14). The more they think the economy is going well, the less they support those policies (idem). Around 28% of the effect of income on that policy preference goes thourgh its effect on perception that inequality is not related to fairness, and around 12% goes through its effect of the perception about the economy.

Now consider the Figure C.15, which uses SEP as an index composed by income and education. The larger the SEP, the more people perceive that the economy is doing well, and the more they perceive that, the more they agree that "Government should spend more on education and training programs for the unemployed and less in benefit". Around 35% of the effect of SEP on preferences for that policy is due to the effect of SEP on that perception about the economy.

Overall, the conclusions in the main paper about the effect of SEP on policy preferences through its effect on perceptions are the same, but the conclusions about which perception, which policy preference, and how much the mechanism explains the effect of SEP on preferences can vary depending on how SEP is constructed.

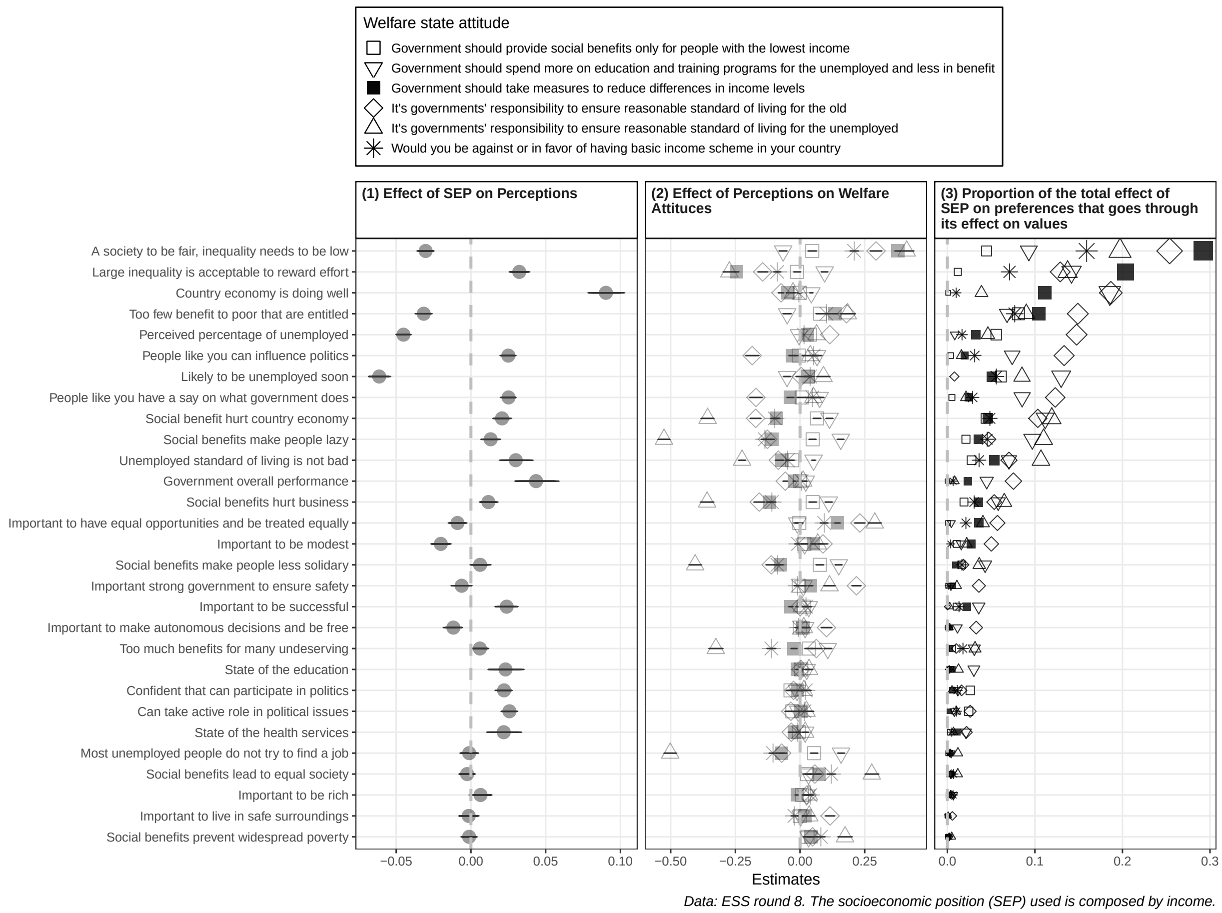


Figure C.14: Association between SEP (income) and perceptions, perceptions and welfare, and the proportion of the effect of SEP on welfare attitudes that goes through different values and perceptions.

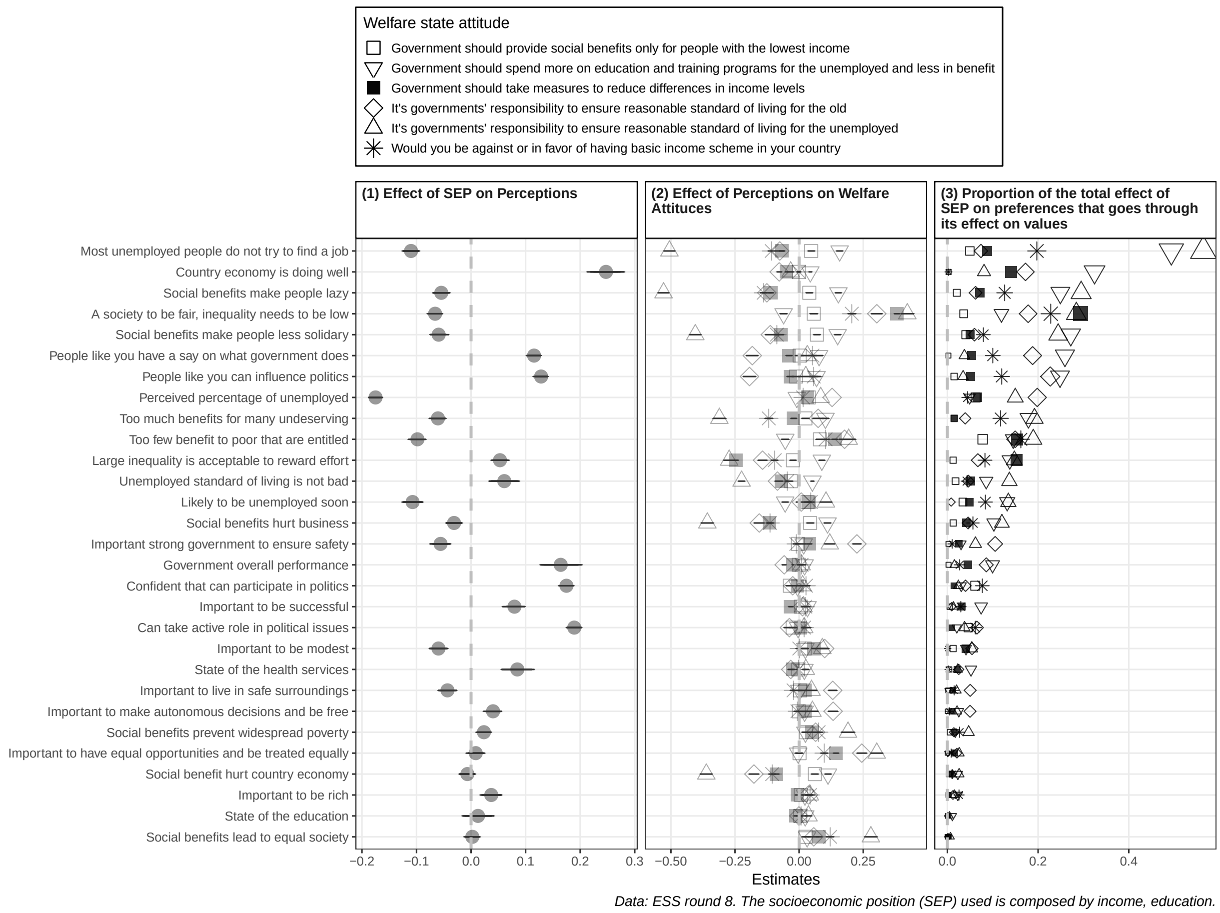


Figure C.15: Association between SEP (income, education) and perceptions, perceptions and welfare, and the proportion of the effect of SEP on welfare attitudes that goes through different values and perceptions.

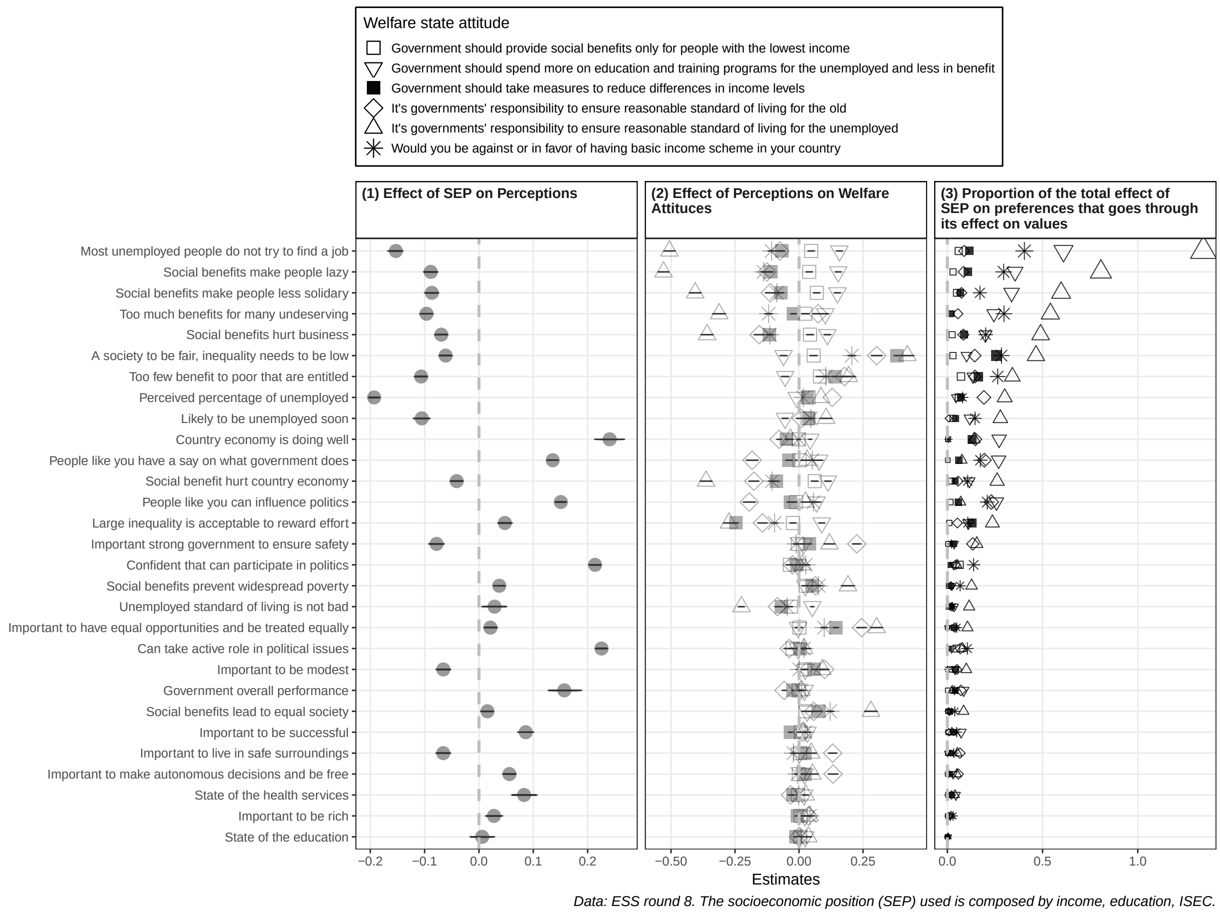


Figure C.16: Association between SEP (income, education, and ISEI-08) and perceptions, perceptions and welfare, and the proportion of the effect of SEP on welfare attitudes that goes through different values and perceptions.

C.2.6 The proportion of the effect of socioeconomic position (SEP) on preferences that goes through its effect on perceptions in each country

The main paper presents the maximum proportion of the effect of SEP on preferences that goes through perceptions for each country. We use here the SEP constructed with income, education, ISEI-08, and age, as in the main paper. The policy considered in the main paper is "Government should provide social benefits only for people with the lowest income". The Tables C.16 to C.20 repeat the exercise for all other policies. The Table C.15 completes the information presented in the main paper with the confidence intervals.

We see that the perception that matters the most vary from country to country and from policy to policy. Consider, for instance, the Table C.16. That Table shows the attitude measured by the question "Would you be against or in favor of having basic income scheme in your country". In Sweden, the mechinism pointed in the paper is 14 times larger than the effect of income alone when we consider the perception that "Too few benefit to poor that are entitled". The larger the SEP, the less people perceive that there are "Too few benefit to poor that are entitled", and the more they agree with that statement, the more they support basic income schemes. If we consider instead the opinions about "It's governments' responsibility to ensure reasonable standard of living for the unemployed" in Sweden (Table C.19), the perception that matters the most is "Large inequality is acceptable to reward effort". The larger the SEP, the more people perceive inequality as acceptable, and the more thay agree that it is acceptable, the less they agree that it's governments' responsibility to ensure reasonable standard of living for the unemployed. Around 65% of the effect of SEP on that policy preference goest through the effect of SEP on perception about how effort can justify inequality. The Tables C.16 to C.20 show that there is a large variance across countries and policies, as discussed in the main paper.

Table C.15: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions.

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Preferences	Proportion of the SEP effect mediated by Perceptions
Spain	A society to be fair, inequality needs to be low	-0.0020	-0.0524 (-0.0918, -0.0129)	0.2972 (0.2522, 0.3422)	7.7866
Portugal	Social benefits hurt business	0.0006	-0.0652 (-0.1167, -0.0137)	-0.0406 (-0.0882, 0.007)	4.4119
Lithuania	State of the economy	-0.0143	0.2626 (0.1059, 0.4193)	-0.0634 (-0.0905, -0.0362)	1.1643
Hungary	Large inequality is acceptable to reward effort	-0.0252	0.0943 (0.0334, 0.1551)	-0.1956 (-0.2346, -0.1566)	0.7319
Estonia	A society to be fair, inequality needs to be low	-0.0761	-0.1277 (-0.1804, -0.075)	0.3311 (0.2789, 0.3832)	0.5556
Slovenia	A society to be fair, inequality needs to be low	-0.1232	-0.2004 (-0.3202, -0.0806)	0.329 (0.1882, 0.4699)	0.5352
United Kingdom	Large inequality is acceptable to reward effort	-0.0485	0.0777 (0.0264, 0.129)	-0.2958 (-0.3377, -0.2539)	0.4739
Austria	Social benefits prevent widespread poverty	0.0272	0.067 (0.0217, 0.1123)	0.1908 (0.1396, 0.2421)	0.4700
Iceland	State of the economy	-0.1291	0.6655 (0.4419, 0.8891)	-0.0889 (-0.1285, -0.0493)	0.4583
Czechia	A society to be fair, inequality needs to be low	-0.2097	-0.1928 (-0.2573, -0.1284)	0.4891 (0.4456, 0.5325)	0.4497
Belgium	A society to be fair, inequality needs to be low	-0.1064	-0.1123 (-0.1591, -0.0655)	0.4242 (0.3723, 0.4762)	0.4477
Netherlands	A society to be fair, inequality needs to be low	-0.1415	-0.0908 (-0.1329, -0.0487)	0.5436 (0.4871, 0.6)	0.3488
Germany	A society to be fair, inequality needs to be low	-0.0936	-0.0763 (-0.1143, -0.0383)	0.4243 (0.3861, 0.4625)	0.3459
Italy	A society to be fair, inequality needs to be low	-0.0739	-0.0779 (-0.118, -0.0378)	0.2997 (0.2612, 0.3383)	0.3159
Poland	A society to be fair, inequality needs to be low	-0.2065	-0.1798 (-0.23, -0.1295)	0.3525 (0.2886, 0.4165)	0.3069
Switzerland	A society to be fair, inequality needs to be low	-0.1543	-0.1028 (-0.1533, -0.0524)	0.389 (0.3294, 0.4485)	0.2592
Ireland	A society to be fair, inequality needs to be low	-0.0961	-0.0693 (-0.1059, -0.0327)	0.3519 (0.3088, 0.3951)	0.2538
Finland	Too few benefit to poor that are entitled	-0.1590	-0.1725 (-0.2075, -0.1376)	0.2063 (0.1521, 0.2605)	0.2238
Sweden	Large inequality is acceptable to reward effort	-0.1202	0.0852 (0.033, 0.1373)	-0.3127 (-0.353, -0.2724)	0.2216
France	A society to be fair, inequality needs to be low	-0.1745	-0.0851 (-0.1281, -0.0422)	0.3358 (0.2929, 0.3788)	0.1638

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

Table C.16: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions; policy 'Ensure basic income for all'

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Preferences	Proportion of the SEP effect mediated by Perceptions
Sweden	Too few benefit to poor that are entitled	-0.0013	(-0.1386, -0.0508)	(0.1046, 0.3061)	14.9553
Belgium	Most unemployed people do not try to find a job	0.0026	(-0.2643, -0.1573)	(-0.1844, -0.0707)	10.3373
Hungary	People like you can influence politics	0.0016	(0.04, 0.1382)	(0.0716, 0.2452)	8.8209
Iceland	Country economy is doing well	-0.0423	(0.3853, 0.8372)	(-0.1733, -0.0658)	1.7281
Italy	People like you have a say on what government does	0.0198	(0.1073, 0.1702)	(0.1184, 0.2951)	1.4497
Lithuania	Important to be modest	-0.0469	(-0.3811, -0.1701)	(0.1027, 0.2312)	0.9808
Netherlands	Perceived percentage of unemployed	-0.0144	(-0.2489, -0.1644)	(-0.0161, 0.1479)	0.9455
Portugal	Confident that can participate in politics	-0.0215	(0.2012, 0.2898)	(-0.1483, 0.012)	0.7776
Finland	Most unemployed people do not try to find a job	0.0334	(-0.2192, -0.1279)	(-0.1934, -0.0863)	0.7267
France	Most unemployed people do not try to find a job	0.0378	(-0.3195, -0.2271)	(-0.1505, -0.0474)	0.7158
Czechia	A society to be fair, inequality needs to be low	-0.0721	(-0.2497, -0.1143)	(0.1966, 0.3243)	0.6573
Spain	State of the education	-0.0079	(-0.2297, -0.0463)	(0.0003, 0.0703)	0.6166
Germany	A society to be fair, inequality needs to be low	-0.0498	(-0.1204, -0.0435)	(0.2635, 0.3693)	0.5203
Poland	Can take active role in political issues	-0.0938	(0.1925, 0.3011)	(-0.2582, -0.0892)	0.4570
Ireland	People like you can influence politics	0.0542	(0.1102, 0.1825)	(0.0851, 0.218)	0.4092
Switzerland	A society to be fair, inequality needs to be low	-0.0849	(-0.1512, -0.0476)	(0.2341, 0.3905)	0.3656
UK	Too much benefits for many undeserving	0.0402	(-0.2209, -0.1279)	(-0.1456, -0.0169)	0.3523
Slovenia	Social benefits make people less solidary	0.1193	(-0.3492, -0.0291)	(-0.3734, -0.0448)	0.3316
Austria	People like you can influence politics	0.1400	(0.0957, 0.1844)	(0.0859, 0.2324)	0.1592
Estonia	A society to be fair, inequality needs to be low	-0.1052	(-0.1847, -0.0779)	(0.0479, 0.2006)	0.1551

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

Table C.17: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions; policy 'Social benefits only for poor while middle and high income are take care of themselves'

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Preferences	Proportion of the SEP effect mediated by Perceptions
Lithuania	Can take active role in political issues	-0.0023	(0.1445, 0.2778)	(-0.2983, -0.0478)	15.8876
Iceland	Important to be rich	-0.0578	(0.1377, 0.4265)	(-0.2073, -0.0537)	0.6369
Austria	Most unemployed people do not try to find a job	-0.0769	(-0.2054, -0.0921)	(0.1076, 0.2129)	0.3102
Sweden	Can take active role in political issues	-0.1618	(0.277, 0.376)	(-0.1774, -0.0287)	0.2078
Czechia	Important to be successful	-0.1455	(0.2784, 0.4128)	(-0.1417, -0.0206)	0.1929
Belgium	Perceived percentage of unemployed	-0.1108	(-0.2459, -0.159)	(0.0202, 0.1528)	0.1581
Germany	Social benefits make people less solidary	-0.1167	(-0.1944, -0.1114)	(0.0722, 0.1683)	0.1576
Poland	Social benefits prevent widespread poverty	-0.1363	(-0.1839, -0.0567)	(0.091, 0.2394)	0.1458
Estonia	Can take active role in political issues	-0.1882	(0.1859, 0.2852)	(-0.1952, -0.0343)	0.1436
Switzerland	Social benefits hurt business	-0.2171	(-0.2409, -0.1268)	(0.0689, 0.2054)	0.1161
Ireland	Confident that can participate in politics	-0.1411	(0.1518, 0.2383)	(-0.1354, -0.0291)	0.1137
Slovenia	A society to be fair, inequality needs to be low	-0.2404	(-0.3029, -0.0526)	(-0.0728, 0.3785)	0.1130
Italy	Large inequality is acceptable to reward effort	-0.1433	(0.0441, 0.1467)	(-0.2209, -0.1164)	0.1122
Finland	Too much benefits for many undeserving	-0.1747	(-0.2058, -0.1269)	(0.0415, 0.1633)	0.0975
Spain	Too few benefit to poor that are entitled	-0.1496	(-0.1608, -0.0663)	(0.0556, 0.1934)	0.0945
Hungary	Important to be modest	-0.1086	(-0.184, -0.0541)	(0.0159, 0.1537)	0.0930
Netherlands	Perceived percentage of unemployed	-0.1506	(-0.2559, -0.172)	(-0.0102, 0.1268)	0.0828
Portugal	Too few benefit to poor that are entitled	-0.2613	(-0.1982, -0.11)	(0.0565, 0.2218)	0.0821
UK	Too much benefits for many undeserving	-0.1711	(-0.2186, -0.1269)	(0.0165, 0.1432)	0.0806
France	Too few benefit to poor that are entitled	-0.1505	(-0.2011, -0.1136)	(0.0025, 0.1154)	0.0616

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

Table C.18: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions; policy 'Ensure standard of living for the old'

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Preferences	Proportion of the SEP effect mediated by Perceptions
Lithuania	State of the health services	0.0023	(0.0624, 0.4064)	(-0.0139, 0.1023)	4.5046
Finland	Confident that can participate in politics	0.0143	(0.1831, 0.2555)	(0.0638, 0.2242)	2.2083
Hungary	People like you can influence politics	-0.0127	(0.042, 0.136)	(-0.3892, -0.115)	1.7667
Estonia	People like you can influence politics	-0.1018	(0.1469, 0.2389)	(-0.4977, -0.2641)	0.7218
Austria	Can take active role in political issues	-0.0867	(0.1791, 0.2781)	(-0.3393, -0.1301)	0.6188
Spain	Important strong government to ensure safety	-0.0542	(-0.1671, -0.0679)	(0.1659, 0.3067)	0.5123
Czechia	A society to be fair, inequality needs to be low	-0.1323	(-0.2587, -0.1312)	(0.2053, 0.3651)	0.4204
Switzerland	Too few benefit to poor that are entitled	-0.0914	(-0.2199, -0.1062)	(0.0786, 0.3433)	0.3763
Sweden	Important strong government to ensure safety	-0.0815	(-0.1888, -0.0624)	(0.1747, 0.3011)	0.3666
UK	Perceived percentage of unemployed	-0.1080	(-0.2506, -0.1598)	(0.1051, 0.2743)	0.3604
Italy	People like you have a say on what government does	-0.1567	(0.1002, 0.1607)	(-0.5056, -0.2786)	0.3263
Iceland	Country economy is doing well	-0.2476	(0.4438, 0.8903)	(-0.1569, -0.0535)	0.2834
Belgium	A society to be fair, inequality needs to be low	-0.1233	(-0.1593, -0.066)	(0.2255, 0.3872)	0.2798
Netherlands	People like you have a say on what government does	-0.1448	(0.1822, 0.2583)	(-0.2787, -0.0717)	0.2666
Portugal	Unemployed standard of living is not bad	-0.1490	(0.1659, 0.3545)	(-0.1998, -0.1005)	0.2621
Ireland	People like you have a say on what government does	-0.2333	(0.1209, 0.1919)	(-0.4616, -0.2926)	0.2528
Poland	A society to be fair, inequality needs to be low	-0.1831	(-0.233, -0.1331)	(0.1247, 0.3791)	0.2518
Germany	Important strong government to ensure safety	-0.2114	(-0.2256, -0.125)	(0.1898, 0.3161)	0.2098
Slovenia	Country economy is doing well	-0.4632	(0.2509, 0.9217)	(-0.2549, -0.0582)	0.1982
France	Too few benefit to poor that are entitled	-0.1749	(-0.1972, -0.111)	(0.0927, 0.2441)	0.1484

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

Table C.19: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions; policy 'Ensure living standard for unemployed'

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Preferences	Proportion of the SEP effect mediated by Perceptions
Lithuania	Most unemployed people do not try to find a job	0.0027	(-0.1897, -0.0255)	(-0.9667, -0.6305)	31.8257
Austria	Social benefits hurt business	0.0013	(-0.1186, -0.0115)	(-0.5778, -0.3413)	22.9800
Finland	Too few benefit to poor that are entitled	-0.0023	(-0.2066, -0.1371)	(0.0556, 0.2526)	11.5173
Switzerland	Social benefits make people lazy	0.0268	(-0.1993, -0.0829)	(-0.5623, -0.3607)	2.4298
Netherlands	Likely to be unemployed soon	-0.0061	(-0.144, -0.0264)	(0.0204, 0.1946)	1.5015
Germany	Most unemployed people do not try to find a job	0.0842	(-0.2512, -0.1673)	(-0.6742, -0.5171)	1.4805
Belgium	Likely to be unemployed soon	-0.0036	(-0.1097, 0.0177)	(0.0065, 0.2119)	1.3953
Sweden	Large inequality is acceptable to reward effort	-0.0523	(0.0279, 0.131)	(-0.536, -0.3551)	0.6765
Slovenia	Likely to be unemployed soon	0.0344	(-0.1354, 0.3867)	(-0.067, 0.4238)	0.6514
Iceland	Unemployed standard of living is not bad	-0.1609	(0.0809, 0.4724)	(-0.4239, -0.2478)	0.5773
France	A society to be fair, inequality needs to be low	-0.0690	(-0.1269, -0.0414)	(0.2883, 0.4649)	0.4590
UK	Large inequality is acceptable to reward effort	-0.0723	(0.0255, 0.1282)	(-0.4197, -0.2355)	0.3484
Italy	Unemployed standard of living is not bad	-0.1504	(0.0545, 0.2263)	(-0.4032, -0.3115)	0.3335
Ireland	Perceived percentage of unemployed	-0.1989	(-0.2333, -0.155)	(0.1859, 0.3741)	0.2734
Hungary	A society to be fair, inequality needs to be low	-0.0688	(-0.1198, -0.0092)	(0.1523, 0.4223)	0.2693
Spain	Unemployed standard of living is not bad	-0.1456	(0.0427, 0.1892)	(-0.368, -0.2568)	0.2489
Portugal	Unemployed standard of living is not bad	-0.3785	(0.1674, 0.3566)	(-0.4134, -0.2866)	0.2423
Czechia	A society to be fair, inequality needs to be low	-0.3198	(-0.2579, -0.1304)	(0.2747, 0.4823)	0.2298
Poland	A society to be fair, inequality needs to be low	-0.3075	(-0.2351, -0.1343)	(0.1855, 0.5076)	0.2081
Estonia	People like you have a say on what government does	-0.2651	(0.1536, 0.249)	(-0.4228, -0.1017)	0.1991

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

Table C.20: Selected indicators of perception in each country based on the maximum proportion of the effect of socioeconomic position (SEP) explained by its effect on perceptions; policy 'Spend more in training program for unemployed and less in unemployment benefits'

Country	Perception	Total effect of SEP on Welfare Preferences[1]	Effect of SEP on Perception	Effect of Percetion on Welfare Preferences	Proportion of the SEP effect mediated by Perceptions
Iceland	Social benefits make people less solidary	-0.0177	(-0.2433, -0.0368)	(0.1352, 0.3461)	1.9038
Hungary	Important to be successful	0.0079	(0.1196, 0.2718)	(0.0032, 0.1285)	1.6300
Netherlands	People like you have a say on what government does	0.0401	(0.1835, 0.2603)	(0.0594, 0.1973)	0.7100
France	Most unemployed people do not try to find a job	-0.0520	(-0.3139, -0.2219)	(0.0913, 0.1841)	0.7094
Estonia	People like you have a say on what government does	0.0542	(0.1562, 0.2528)	(0.0998, 0.2682)	0.6942
Switzerland	People like you can influence politics	0.0204	(0.1596, 0.2796)	(-0.0062, 0.1148)	0.5845
Sweden	Country economy is doing well	0.0519	(0.2468, 0.4477)	(0.0502, 0.1178)	0.5621
Lithuania	People like you can influence politics	0.0580	(0.0853, 0.2256)	(0.0671, 0.3015)	0.4938
Finland	Too few benefit to poor that are entitled	0.0577	(-0.2092, -0.1386)	(-0.1762, -0.0509)	0.3424
Italy	Important to be rich	0.0539	(0.1708, 0.2797)	(0.0249, 0.1098)	0.2817
UK	People like you have a say on what government does	0.0768	(0.1052, 0.1879)	(0.0703, 0.1925)	0.2508
Spain	Too few benefit to poor that are entitled	0.0552	(-0.1627, -0.0666)	(-0.1869, -0.0545)	0.2508
Germany	Country economy is doing well	0.0741	(0.292, 0.4603)	(0.0262, 0.0714)	0.2477
Slovenia	Country economy is doing well	0.2215	(0.2505, 0.9537)	(-0.0002, 0.1535)	0.2085
Ireland	Country economy is doing well	0.0555	(0.1987, 0.3704)	(0.0089, 0.0551)	0.1641
Czechia	A society to be fair, inequality needs to be low	0.1313	(-0.2571, -0.1266)	(-0.1648, -0.0458)	0.1538
Belgium	People like you can influence politics	0.0903	(0.1719, 0.2538)	(-0.0031, 0.1248)	0.1433
Austria	Important to be successful	0.1133	(0.1858, 0.3146)	(0.0068, 0.1091)	0.1279
Poland	Social benefits make people lazy	0.0833	(0.0332, 0.1638)	(0.0311, 0.174)	0.1213
Portugal	Unemployed standard of living is not bad	0.0883	(0.1699, 0.3642)	(-0.0121, 0.061)	0.0738

Estimation included the folowing controls: perception (column 2), occupation unemployment risk (OUR), gender, unemployed, union, religion
[1] Effects obtained when we omitt indicators of perception.

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