



**Has the Attitude of U.S. Citizens Towards Redistribution Changed Over Time?**

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# Has the attitude of US citizens towards redistribution changed over time?

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## Abstract

Demand for redistribution has been traditionally investigated within a static scenario, giving the perception of a stationary association between individual determinants and preferences. Using survey data from GSS over the period 1978-2010, we model individual preferences in the U.S. within a chronological perspective. We fit a logistic non-nested multilevel model with different levels of variation. Metodologically, we propose a way to model individuals, time and cohort simultaneously and face some challenges in estimation due to complex covariance structures. Empirically, despite an overall stable trend in demand for redistribution, we find that driving factors in shaping redistributive preferences have changed rapidly.

Keywords: Individual preferences, demand for redistribution, multilevel models, time-varying slopes models, weakly informative priors. JEL classification C5, D3

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# 1 Introduction

Public support for social spending to alleviate income differences between rich and poor is an essential pillar of mature welfare systems, and the more so in periods of crisis such as the recent Great Recession. An extensive literature has investigated individual and contextual factors that can help explain citizens' attitudes towards the role of the government in redistributive policies<sup>1</sup>. Based on the assumption that economic self-interest is the main factor in shaping preferences, current personal income as well as prospects of economic mobility (in both directions) have been regarded as strong predictors of individual attitudes towards redistribution (Ravallion and Lokshin, 2000; Benabou and Ok, 2001; Alesina and La Ferrara, 2005; Milanovic, 2000 and 2010). Self-interest driven individuals may also take redistribution and transfer spending as a form of insurance against uncertainty about future incomes due to insecurity in the labor market: the higher the uncertainty of future income, namely, the higher an individual's risk exposure, the more the individual is expected to increase the demand for government protection (Rehm, 2009). This strand of literature broadly identifies two main sources of insecurity (Iversen and Soskice, 2001; Cusack *et al.*, 2006): risk of unemployment and potential devaluation of workers' skills. More generally, disadvantaged groups in the labor market, typically women and the less educated, are, *ceteris paribus*, more likely to support redistribution. Additionally, the underlying dynamics of attitudes towards redistribution can reflect polarization spread across a broad set of beliefs. Beliefs in regards to the causes of inequality, concern for fairness, religious convictions, forms of altruism, as well as social norms about what is acceptable or not in terms of inequality and poverty, have been suggested as driving forces behind the formation of re-distributional preferences (Feong, 2001; Alesina and La Ferrara, 2005; Benabou and Tirole, 2006). Party identification, as well as class, ethnicity, and religious affiliation are thought to be relevant for mapping such beliefs and thus identifying people's preferences. Scheve and Stasavage (2006) argue that religion and social spending are viewed as substitute mechanisms that insure individuals against adverse economic events, like unemployment or shocks to income. Therefore

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<sup>1</sup>See Alesina and Giuliano (2011) for an exhaustive review.

people who frequently attend religious functions, irrespective of their creed, rationally prefer less social spending since psychological benefits from religion would compensate the monetary cost associated with an adverse event. The idea that preferences of redistribution depend upon its effect on the relative standard of living of the individual (Corneo and Grüner, 2002) motivates the importance of ethnic (and possibly religious) heterogeneity in forming attitudes towards redistribution. Alesina and Glaeser (2004) state that individuals who belong to one ethnic group are less willing to support redistributive programmes that are perceived to benefit other ethnic groups. Group loyalty (Lüttmer, 2001), differences in status, and ethnicity have been suggested playing an important role in shaping redistributive preferences.

The majority of the studies, including those quoted above, have also provided empirical evidence of the association between a variety of determinants and attitudes towards redistribution in developed and developing countries, in some cases underlying the main differences across countries or across continents (see e.g. Finseraas, 2009; Massari *et al.*, 2013).

Analyses of determinants of preferences, however, are mostly concerned with a static period of time and create the perception of stationary association between determinants and preferences. While it seems questionable to assume the invariance of such effects over time, there has not been much work on changes of correlates over time within a single country. This paper aims to frame the analysis of individual determinants of preferences in the United States within a chronological perspective. We use repeated cross-sectional data from the General Social Survey (GSS) over the period from 1978 to 2010, as well as multilevel models that are able to capture temporal patterns net of age and cohort effects. More specifically, the empirical questions our paper wishes to address are the following: Has overall propensity towards redistribution increased or decreased in the U.S. over the past few decades? To what extent have associations between individual determinants (such as income, education, race, gender,..) and attitudes towards redistribution varied over time? Is it possible to identify trend patterns? Do temporal patterns actually reflect cultural and economic changes in the country affecting individuals of all ages (period

effects) or are they due to the stratification of different generations in the sample (cohort effects)? By modeling the effects of time we show that in the U.S., despite a near flat trend in the overall demand for redistribution, the role of some individual predictors has changed over time and empirical findings and conclusions partially depend on which time-window is chosen for the analysis.

The rest of the paper is organized as follows. Section 2 describes the attitudes towards government redistribution and the individual characteristics that, according to the existing literature, are expected to be strong predictors of the demand for redistribution, and also provides some descriptive statistics. Section 3 discusses the representation, interpretation and estimation of multilevel models and the empirical strategy employed in the process. Section 4 reports the main empirical results. Section 5 summarizes and concludes.

## 2 Data description

Data is in the form of repeated cross-section independent samples coming from the General Social Survey (GSS). The GSS is an ongoing nationally-representative survey that has been conducted by the National Opinion Research Center (NORC) annually (with some exceptions) since 1972 and bi-annually since 1994. We use all the data available from 1978, year in which the question on redistribution was introduced, to 2010, spanning a period of 32 years.

The variable that captures individual support for redistribution is derived from the GSS question (coded as EQWLTH), that states:

*“Some people think that the government in Washington ought to reduce the income differences between the rich and the poor, perhaps by raising the taxes of wealthy families or by giving income assistance to the poor. Others think that the government should not concern itself with reducing this income difference between the rich and the poor”.*

The exact wording of this question has been retained to facilitate temporal analyses, allowing U.S. to combine in a single dataset the single-year surveys and model time as a

covariate. Respondents could choose on a 1 to 7 scale from 1 = “Should” to 7 = “Should not”. Overall the number of respondents to the question is 23,765.

Since data is organized as time-series cross-section, respondents can be nested within cells created by the cross-classification of two types of social context: birth cohorts and survey years. A “cohort” is generally defined as a group with a fixed membership over time. A birth cohort is based on the birth year of individuals, and observations in a given cohort are considered to display similar features due to similar habit formation (exposure risk). Table 1 displays such structure, where a five-year bandwidth is used to construct the cohorts. Rows in the table represent years, and columns cohorts. Each cell shows the number of individuals born within a certain time period and interviewed in a given year. As will be clear in the methodological section below, survey years and birth cohorts are level-2 contextual variables in our hierarchical model.

We defined attitude towards redistribution according to a binary variable,  $Y_i$ , which is equal to 1 if respondent  $i$  thinks that government should reduce difference in income levels and 0 otherwise. More specifically,  $Y_i$  takes value 1 if  $EQWLTH < 4$  and zero otherwise. To be conservative, we also recoded to 0 the central category, which represents very bland support. Figure 1 reports the pattern of propensity towards redistribution in the U.S.. Support for redistribution was 48.1% in 1978, reaching a peak in 1990 (52.6%) and a minimum in 1994 (40.3%), showing an increase until 2008 (49.4%) and a drop in 2010 (42.3%). However, there is no clear evidence of a changing-time pattern but rather a near flat trend for the whole period. There is instead a substantial variation in individual preferences across birth cohorts. This cohort heterogeneity suggests the importance of adequately accounting for cohorts in modeling preferences.

From the GSS dataset we also extract a set of personal characteristics that the literature has shown to have a significant effect on the demand for redistribution. The selected individual predictors include: equivalent income, defined as total family income before taxes, from all sources, of the year previous to the interview, size-adjusted using the Luxembourg Income Study equivalence scale<sup>2</sup>; age (reported in single years at last birthday);

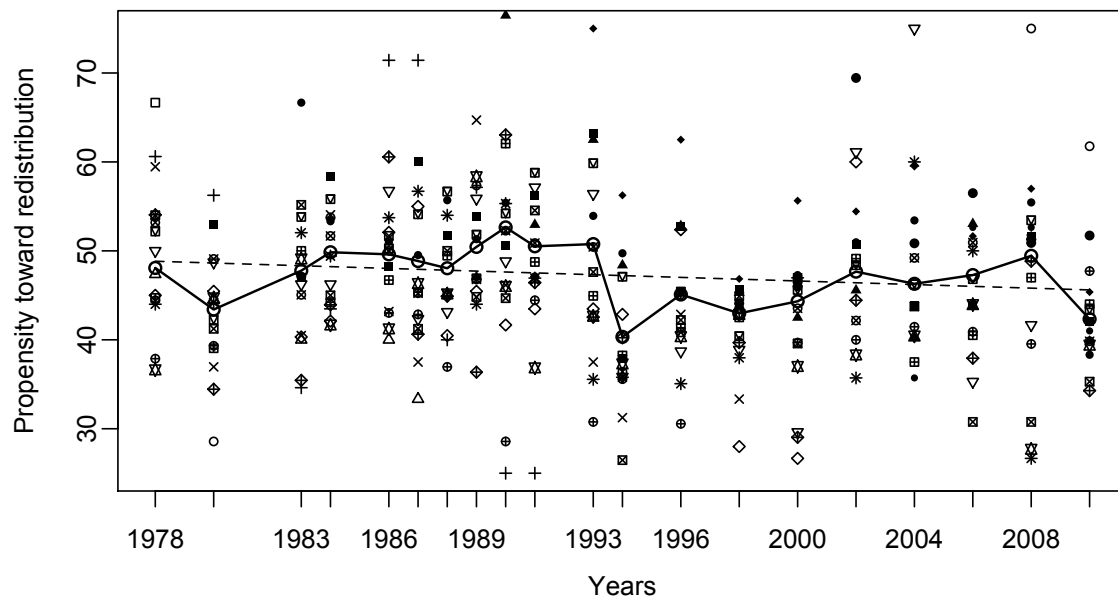
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<sup>2</sup>In the surveys, income levels are bracketed and refer to current value. Each respondent is asked to indicate in which category her/his total annual family income falls. Number of categories and upper and

Table 1: Respondents to question EQWLTH of the GSS by year of the survey and birth cohort

Cohort → Survey year ↓	1885	1890	1895	1900	1905	1910	1915	1920	1925	1930	1935	1940	1945	1950	1955	1960	1965	1970	1975	1980	1985	1990	Total
1978	3	9	19	33	37	40	38	50	50	37	66	71	85	94	46	0	0	0	0	0	0	0	678
1980	0	7	18	32	46	88	78	97	86	90	89	123	169	165	142	51	0	0	0	0	0	0	1281
1983	0	2	10	26	42	62	80	87	98	79	104	110	158	182	223	102	6	0	0	0	0	0	1371
1984	0	0	6	23	37	57	80	80	85	66	93	108	156	149	172	161	15	0	0	0	0	0	1288
1986	0	0	5	14	44	48	74	89	67	71	86	114	137	164	183	139	49	0	0	0	0	0	1284
1987	0	0	6	21	32	60	85	97	97	96	105	136	172	210	207	190	105	0	0	0	0	0	1619
1988	0	0	5	5	19	42	51	60	50	49	46	62	93	102	90	116	79	1	0	0	0	0	870
1989	0	0	0	14	17	33	34	58	50	44	68	72	81	109	110	115	76	17	0	0	0	0	898
1990	0	0	0	4	13	24	43	47	47	46	28	50	87	88	107	83	74	17	0	0	0	0	758
1991	0	0	0	4	15	23	42	44	49	56	45	57	80	114	131	96	87	34	0	0	0	0	877
1993	0	0	0	5	8	23	39	42	45	47	52	68	89	113	132	106	89	56	4	0	0	0	918
1994	0	0	0	0	16	28	53	68	95	87	104	118	170	195	223	240	185	93	16	0	0	0	1691
1996	0	0	0	0	14	21	31	45	77	82	72	114	162	169	196	203	187	161	56	0	0	0	1590
1998	0	0	0	0	3	25	36	49	79	63	68	98	127	163	198	206	168	170	111	2	0	0	1566
2000	0	0	0	0	0	15	27	48	66	62	63	100	126	147	182	190	165	160	133	50	0	0	1534
2002	0	0	0	0	0	5	18	18	28	36	35	47	57	83	93	75	104	79	79	36	0	0	793
2004	0	0	0	0	0	0	4	16	25	16	41	47	64	63	80	98	73	77	79	59	14	0	756
2006	0	0	0	0	0	0	17	39	42	58	66	91	116	161	173	178	170	181	151	154	57	0	1654
2008	0	0	0	0	0	0	12	13	30	43	43	65	83	113	131	120	101	128	93	112	76	4	1167
2010	0	0	0	0	0	0	0	17	24	35	44	66	75	123	113	107	107	103	108	116	100	34	1162
Total	3	18	69	181	343	594	842	1064	1190	1163	1318	1717	2287	2707	2932	2576	1840	1277	830	529	247	38	23765

Figure 1: Pattern of propensity towards redistribution in the U.S.: 1978–2010. Propensity towards redistribution is calculated as the percentage of respondents that agree with the statement that Government should reduce income differences.



*Source:* authors' calculation on weighted data from GSS.

The solid line represents national average.

The dotted line represents the estimated linear trend.

Different symbols represent different cohorts in each year of the interview.



gender; marital status; children living in the family; race (categorized as white, black, asian & hispanics); years of education completed (recoded in three classes: less than 12 years, between 12 and 16, more than 16 years); employment status; past experience of unemployment in the last ten years; religious denomination (protestant, catholic, other denominations, not religious); religious attendance (recoded as a binary variable equal to 1 whether the individual goes to religious functions at least once a week); and political views (categorized as close to democrats, close to republicans, not close to democrats or republicans).

### 3 Modeling individual preferences over time

#### 3.1 Empirical specification

Preferences for redistribution have been traditionally modeled by pooling data coming from repeated cross-sectional surveys in which differences between years have been either ignored or modeled by including time-dummies. The main advantage of this procedure is to increase the number of observations with a consequent improvement of estimates precision, but at the cost of losing sight of the dynamics of the phenomenon. For example, demand for redistribution may have changed over time and/or determinants with a strong influence in the past may have lost their importance in favor of other substantive determinants. The most straightforward way to detect whether the relative impact of predictors has changed over time is to conduct separate analyses. One can imagine fitting separate regression models for each year and then running a meta-regression using the estimated coefficients for each year as dependent variable and time as predictor. Fitting a model separately for each year, that is using a non-pooling model, can produce useful results, as we describe later, however estimates of time-varying effects can be “noisy” due to insufficient observations and sparseness of data, a well-known problem that arises when dealing with separate datasets (Gelman and Hill, 2007). Multilevel models (MLM),

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lower bounds vary over time. We consider midpoints of each categories as a proxy of actual total income. For top income categories that do not have upper limit we imputed the values based on the Pareto curve (Hout, 2004). All figures are deflated by the national consumer price index and are at 2000 prices. The LIS equivalence scale is the square root of the number of household members.

considered as “partial pooling” models (a compromise between un-pooled and completely pooled models) represent a considerable improvement over separately estimated models since they provide more accurate estimates of time-series effects than un-pooled analyses, as well as more realistic representation of uncertainty than conventional pooled analyses (Shor *et al.*, 2007). The amount of pooling depends on the variance across years and information available for each year. This is because multilevel estimates are weighted: a weighted average of the specific regression estimates in each year and of the overall regression coefficient estimated pooling together all the years. They are also known as *shrinkage estimates*. This shrinkage weight allows for more tightly clustered time-series coefficients and superior out-of sample predictions compared to separately run regressions (Western, 1998).

Multilevel models explicitly take into account the hierarchical structure of the data by assuming different relations for different clusters. The structure of our data refers to individual observations that are nested (clustered) not only within survey time periods but also within cohorts, producing a cross-classified structure. If this structure is not taken into account, what may appear to be historical time-period variation could actually be between-cohort variation and vice versa<sup>3</sup>. Assessing the relative importance of substantial period or cohort effects is a problem we explicitly address. In this task we follow the work of Yang and Land (2006, 2008) and Yang (2008) who applied cross-classified multilevel models to age-cohort-period (ACP) analyses in the context of repeated cross-sectional surveys.

The binary outcome is modeled with a non-nested multilevel logistic regression that can be used to deal simultaneously with temporal and generational patterns. Individual  $i$  is characterized by (nested in) period  $t$  of the interview and birth cohort  $k$ . The probability  $P(Y_i = 1) = \pi_i$  of individual  $i$  to be in favor of redistribution can be modeled as:

$$\pi_i = \text{logit}^{-1}(\alpha_{t[i],k[i]} + \beta_{t[i],k[i]}x_i), \text{ for } i = 1, \dots, n. \quad (1)$$

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<sup>3</sup>An identification problem arises due to the exact linear relationship between age, cohort and period (ACP) effects. An extensive body of literature has provided different solutions to the ACP identification problem (see e.g. Mason and Fienberg, 1985; Deaton and Paxson, 1994; Attanasio, 1998).

where  $\text{logit}^{-1}(z) = \frac{1}{1+e^{-z}}$  is the inverse-logistic function,  $x$  is an individual-level predictor, e.g. personal income,  $\alpha_{t[i],k[i]}$  and  $\beta_{t[i],k[i]}$  are the varying coefficients of the model, with subscript  $t[i]$  and  $k[i]$  indexing, respectively, the year  $t$  of the interview and the cohort  $k$  of the respondent  $i$ . The model is a *varying-intercepts* and *varying-slopes* model since we are interested not only in variations of the intercept but also in variations of the influence of the single predictor(s) on the outcome. The source of variations of the coefficients is twofold: time and cohort. Therefore in the second level of the model intercepts and slopes are decomposed into terms that vary with time and cohort. Assuming no interactions between them, we have:

$$\begin{pmatrix} \alpha_{t,k} \\ \beta_{t,k} \end{pmatrix} = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} + \begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} + \begin{pmatrix} \alpha_k \\ \beta_k \end{pmatrix} \quad (2)$$

The year and cohort coefficients are assigned a multi-normal probability distribution with mean vector and covariance matrix to be estimated from the data:

$$\begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} \sim \text{MN} \left( \begin{pmatrix} b_0 t \\ b_1 t \end{pmatrix}, \Sigma \right), \text{ for } t = 1, \dots, T \quad (3)$$

$$\begin{pmatrix} \alpha_k \\ \beta_k \end{pmatrix} \sim \text{MN} \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Omega \right), \text{ for } k = 1, \dots, K \quad (4)$$

where  $MN$  is a multi-normal distribution. The  $\alpha_t$  coefficients include a linear trend to capture the overall increase/decrease of the demand for redistribution during the period under study, while the linear trend included in the  $\beta_t$  coefficients intends to capture possible (linear) changes in the association between the outcome and the predictor(s) over time to the extent supported by the data.  $\Sigma$  represents the covariance matrix for the random time-varying intercepts and slopes, while  $\Omega$  is the covariance matrix representing the variation of intercepts and slopes in the population of cohorts.

To represent our general model, it is convenient to move to matrix notation in which there are  $T$  time periods,  $K$  birth cohorts,  $P$  individual-level predictors whose coefficients

vary by group (including varying intercepts) and  $R$  individual-level predictors with unmodeled coefficients. We also include calendar time as group-level predictor in the group-level regressions of time-varying coefficients:

$$\begin{aligned}\pi_i &\sim \text{logit}^{-1}(X_i^0 B^0 + X_i B_{t[i],k[i]}), \text{ for } i = 1, \dots, n \\ B_{t,k} &= B_0 + B_t + B_k \\ B_t &\sim \text{MN}(U_t G, \Sigma) \text{ for } t = 1, \dots, T \\ B_k &\sim \text{MN}(0, \Omega), \text{ for } k = 1, \dots, K,\end{aligned}$$

where  $X^0$  is the  $n \times R$  matrix of individual predictors,  $B^0$  the  $R$ -vector of their unmodeled regression coefficients;  $X$  is the  $n \times P$  matrix of individual predictors (the first column is a column of 1's) that have coefficients varying by groups.  $B_{t[i],k[i]}$  is the  $P$ -vector of the modeled regression coefficients for the cross-classified groups that include unit  $i$ .  $B_{t,k}$  can be decomposed into the sum of  $B_t$  and  $B_k$ , along with the group-level intercepts  $B_0$ .  $U_t$  is the  $t$ -th row of the matrix of group-level predictors and  $G$  is the associated matrix of group-level regression coefficients.  $\Sigma$  and  $\Omega$  are the covariance matrices for the random coefficients.

### 3.2 Estimation strategy

Our model is particularly challenging in terms of estimation since we have three levels of variations (first level coefficients that vary by time and cohort), implying complex covariance structures. It can be the case that the estimated group-level covariance matrices are singular, implying underestimation of uncertainty in the parameter estimates of the model. We fit the model using marginal likelihood estimates, where random effects are treated as nuisance parameters by integrating them out. Logistic multilevel models can be estimated by approximating the integral in the likelihood with different methods (PQL, Laplace, adaptive Gaussian quadrature). However, given the complexity of our model, these approaches suffer from very slow convergence and unexpected features that can occur due to regularization problems of the covariance matrices. Therefore, we adopted

the maximum penalized likelihood (MPL) approach recently suggested by Chung *et al.* (2012) to regularize the covariance matrix<sup>4</sup>, say  $\Psi$ , away from its boundary  $|\Psi| = 0$ . In multivariate cases, Chung *et al.* recommend adding as penalty term in the penalized log-likelihood function the log-Wishart on the covariance matrix  $\Psi$ , which is equivalent to the sum of log-gamma penalties on the eigenvalues of  $\Psi^{1/2}$ . With a certain choice of parameters, the use of a Wishart distribution shifts the estimate of each eigenvalue away from zero, that is, it keeps the variances away from zero and the correlation matrix positive definite. The exponential of the penalty term can be regarded as a bayesian prior density for  $\Psi$  and the MPL estimates can be viewed as posterior *modal* estimates. The Wishart prior is weakly informative, in the sense that the log-likelihood at the maximum penalized likelihood estimates tends to be not much lower than the maximum since the priors supply some directions but still allow inference to be driven by the data (Chung *et al.*, 2012)<sup>5</sup>.

Continuous inputs are mean centered and scaled by two times their standard deviation. Centering predictors in multilevel models reduces the correlation between (slope and intercept) random effects, and this makes it possible to interpret the magnitudes of one set of random effects separate from the others and to improve the numerical stability of the estimation algorithm. Standardization is obtained by dividing the centered inputs by two standard deviations, so that the resulting coefficients can be interpreted roughly in the same way as those of binary predictors (Gelman, 2008).

Since the main goal of our paper is to investigate the behavior of preference determinants over time, we first identify which are the predictors with time-varying pattern, i.e. which coefficients should be treated as random and then which of the possible covariances between errors should be estimated. The reason for this step is, that, having our model a large number of predictors, passively assuming all parameters to vary randomly could result in an excessively and unnecessarily complex model. Instead, we identify the random

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<sup>4</sup>Note that in our model there are two covariance matrices,  $\Sigma$  and  $\Omega$ .

<sup>5</sup>We used the `bg1mer` function in the `blme` package available in the R Archive network (R Development Core Team, 2012), in which scale matrix and degrees of freedom of the Wishart distribution are chosen suitably enough to obtain a weakly informative prior distribution. We thank Vincent Dorie for his useful comments and discussions.

coefficients by fitting a model separately for each year and then examine the estimated coefficients of the predictors. Coefficients that are prime candidates for being treated as fixed are those that are small in size and almost un-varying over time.

## 4 Empirical results

In this section we extensively discuss those time and cohort varying coefficients that exhibit a strong association with the propensity towards redistribution in the United States. However, our model also incorporates unmodeled individual-level coefficients  $B^0$ , a vector of coefficients which, by assumption, are common to all the years and birth cohorts, along with a vector of coefficients  $B_{t,k}$  that are further modeled over time and cohort (*cfr* eq. 2).

### 4.1 Unmodeled coefficients

The coefficients of some predictors did not show variability over time and for this reason they have been left unmodeled<sup>6</sup>. We left unmodeled those coefficients whose size was small and their pattern over time (and over birth cohort) was almost stable. Figure 2 reports the “population-average” model; that is, the estimated  $B^0$  and the estimated part of  $B_{t,k}$  that do not vary. Specifically, the estimated vector  $\hat{B}_0$  of the unmodeled coefficients includes marital status, gender, religion, religion functions attendance, employment status and previous spells of unemployment.

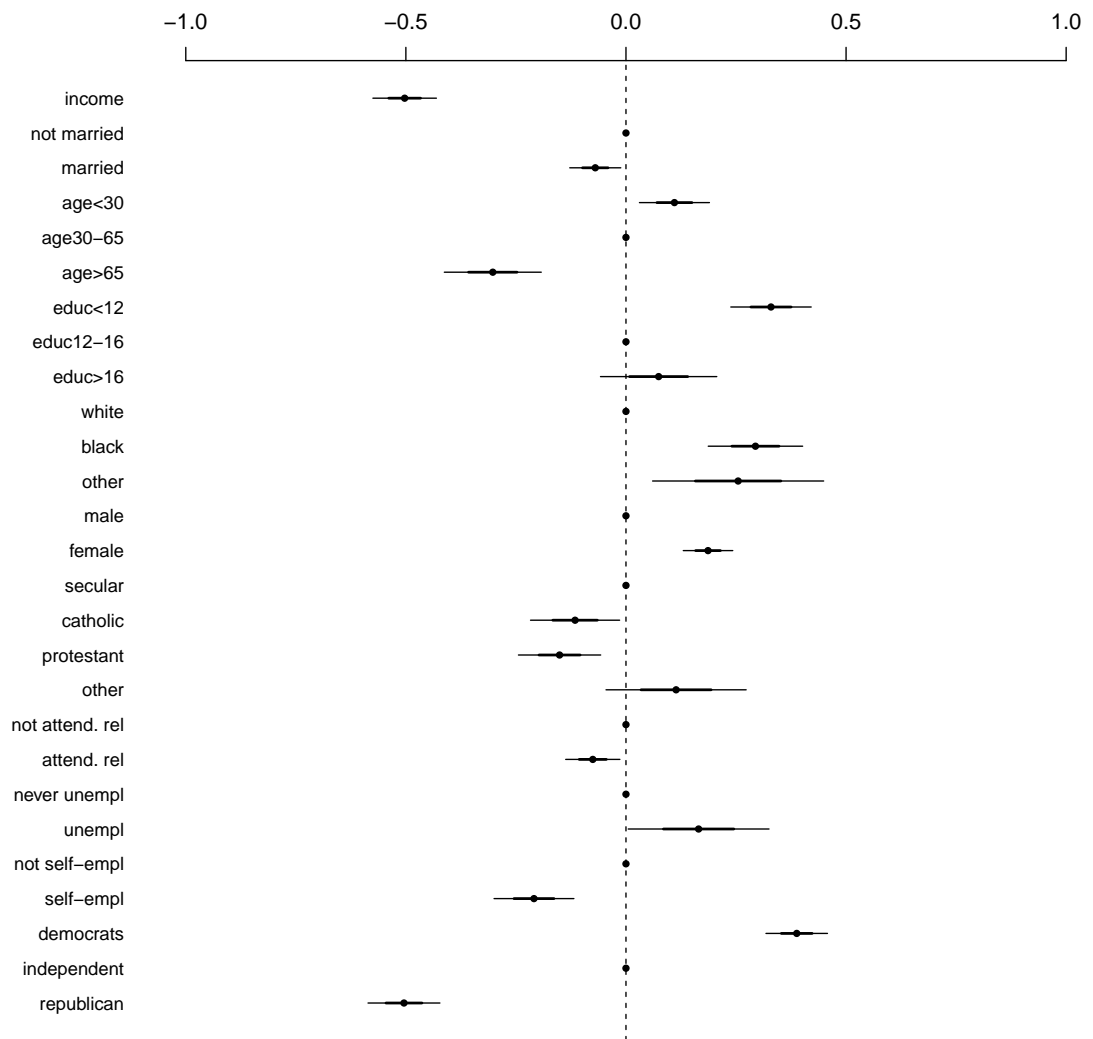
Consistently with the findings of previous studies, women disproportionately favor redistribution, with no significant variation over time. The estimated difference between women and men in the predicted probability of supporting redistribution is at the maximum<sup>7</sup> 5%. Being married has a slight negative effect on the support for redistribution. *Ceteris paribus* being self-employed reduces by approximately 5% the likelihood of being in favor of redistribution steadily over time, while having experienced a period of unem-

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<sup>6</sup>For this reason our model refers to the class of mixed-effect models.

<sup>7</sup>We applied the “divide by 4 rule” to get an upper bound of the predictive difference in the probability of being in favor of redistribution moving from the baseline category to the comparison category (Gelman and Hill, 2007, p. 82).

Figure 2: Estimated coefficients with relative  $\pm 2$  standard errors of individual characteristics in the U.S. 1978–2010: varying-intercept and varying-slope multilevel logistic regression. Dependent variable: Government should reduce differences in income levels. Respondents are nested within periods and birth cohorts.



ployment develops positive attitudes to redistribution (an expected increase of around 4%). Religious affiliation has a small significant effect on people’s attitudes towards redistribution: being Catholic or Protestant translates into less demand for redistribution than secular individuals (-3%). Moreover, religious functions attendance slightly reduces the probability of support, accordingly with the findings of Scheve and Stasavage (2006).

## 4.2 Age

To better illustrate age effect on preferences the age variable has been codified into three different classes: individuals aged less than 30 years old, individuals aged between 30 and 65, which is our reference class, and individuals aged 65 and over<sup>8</sup>.

Younger individuals are on average more likely to favor redistribution than adults (+2.5%). This effect is statistically significant and does not vary over time. Senior citizens are instead more adverse to redistribution than middle-aged individuals and their opinions have significantly changed over time. Figures 3 and 4 show the estimated time effects ( $\hat{\beta}_t^{\text{age}}$ ) and birth cohort effects ( $\hat{\beta}_k^{\text{age}}$ ) for individuals aged over 65 net of all other factors, time and cohort included, versus time and birth cohort respectively.

Figure 3 shows a pronounced negative trend pattern, indicating that in the U.S. support for redistribution among older people has decreased in the last four decades: people aged 65 and over tend to be more adverse to redistribution than they were in the past. While in the late 1970s there was a negligible difference between old and middle-aged people, in 2010 being old reduces the likelihood of being in favor of redistribution by more than 10%. This estimated effect is represented in the figure through a linear trend, highlighting this behavior even further. A different picture is captured by Figure 4: attitudes towards redistribution among senior interviewees are quite stable with respect to their birth cohort, and close to the population average value of  $-0.30$ , with two peaks for people born in 1915-1920 and 1935-1940. However, there is no clear evidence of a plausible linear cohort effect. The estimated effects for the last cohorts are complete pooling estimates since people born after 1946 cannot be classified as old.

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<sup>8</sup>Our findings are robust to alternative specification of the variable, also when allowing for concavity introducing age and age squared.



Figure 3: Estimates and standard errors of time-varying beta coefficients  $\hat{\beta}_t$ : individuals aged 65 and over, along with the estimated multilevel regression line  $\beta_t^{\text{age}} = b_0 + b_1 t$ .

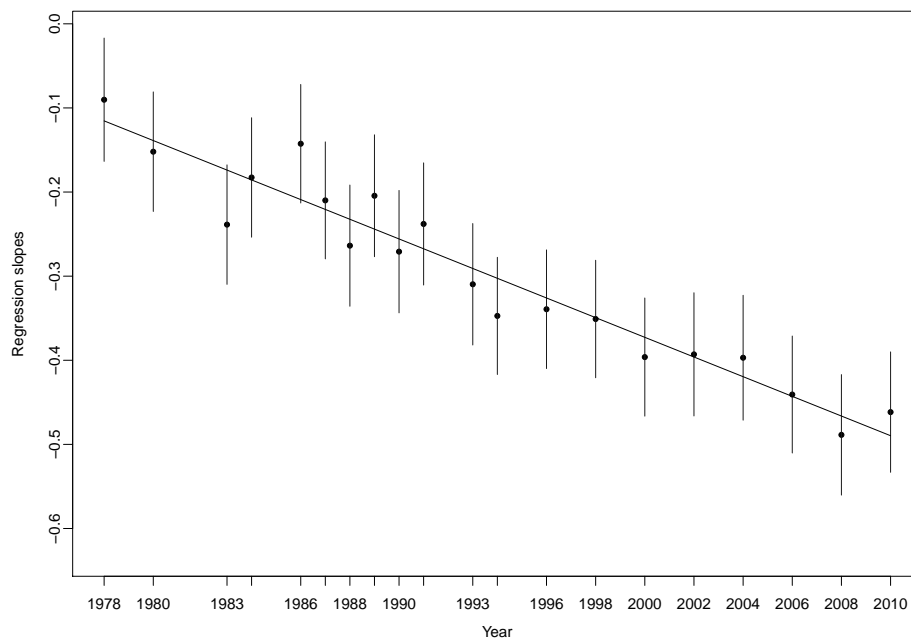
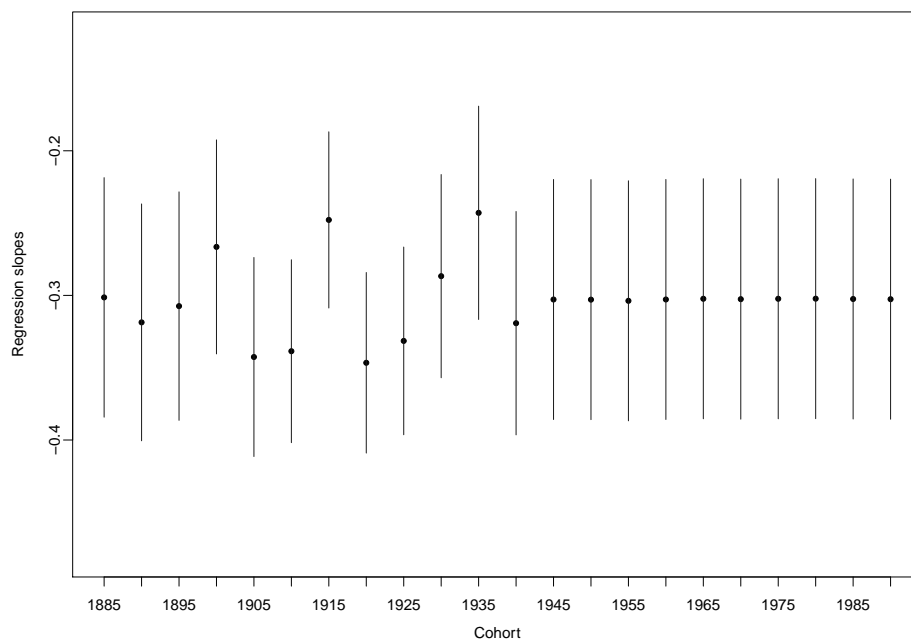


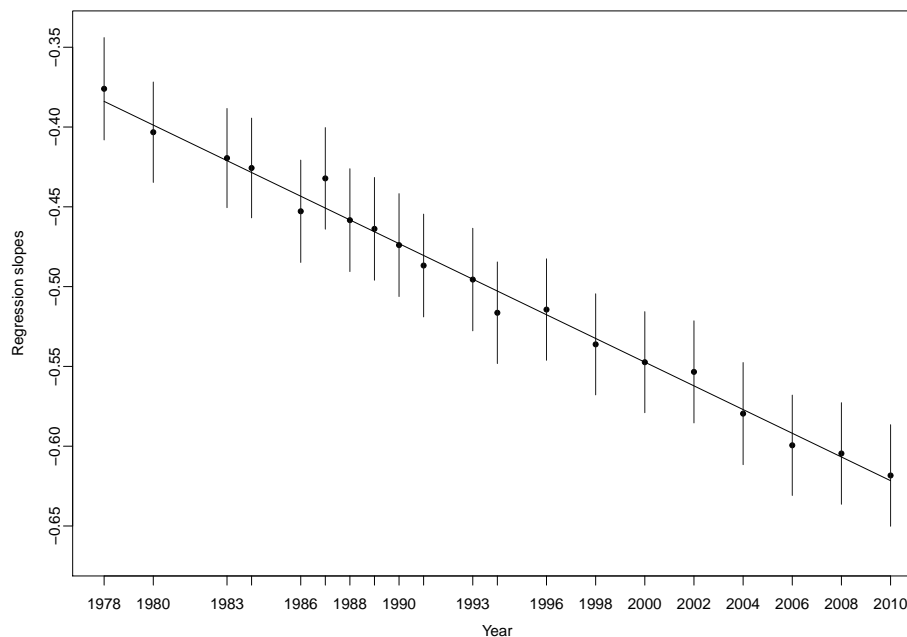
Figure 4: Estimates and standard errors of birth cohort-varying beta coefficients  $\hat{\beta}_k$ : individuals aged 65 and over.



### 4.3 Income

We have already learned from Figure 2 that, all things being equal, richer people in the U.S. are more adverse to redistribution. The estimated income slope is on average  $\beta^{\text{income}} = -0.50$ , meaning that a movement along the equivalent income scale of two times the standard deviation, roughly corresponding to an increase of 74,000 dollars, reduces the probability of supporting redistribution by approximately 13%. What about rich and poor individuals over time and across cohorts? Our evidence shows that income effect varies over time but is not influenced by birth cohort. A strong temporal pattern occurs when we examine the predictive power of income over the last thirty years. Income matters more at the end of the period than in the 1970s. Figure 5 reports the time pattern of income slopes  $\hat{\beta}_t^{\text{income}}$  ( $t = 1978, \dots, 2010$ ) along with their estimated linear trend. The systematic differences between rich and poor individuals have constantly risen in the past thirty years, indicating a stronger impact of income in shaping people's attitude towards redistribution<sup>9</sup>. Cohort effect is instead negligible in size.

Figure 5: Estimates and standard errors of time-varying beta coefficients  $\hat{\beta}_t$  for family income: the estimated trend effect is represented by the continuous line.



<sup>9</sup>Results are robust to the coding of income and to different choices of measurement.

As an alternative perspective, we analyzed time differences between poor and rich on the probability scale. Simple predictive comparison is straightforward when we deal with a small number of inputs: for example comparing individuals with two different levels of income, holding identical all other characteristics, usually fixed at the mean or at the median of the data. However, with a high number of predictors this approach becomes problematic: single central values are not necessarily representative of the entire distribution especially for inputs whose values are very spread out; when many of the inputs are categorical the concept of “central value” becomes less meaningful and since logistic regression is not linear the choice of reference points for evaluating changes in probabilities is quite arbitrary. Further complications arise with multilevel models. Therefore, we opted computing an *average predictive comparison*, which is the average of the predictive differences in probability over the  $n$  observations in the data (Gelman and Pardoe, 2007). The predictive difference of individual  $i$  for the input of interest  $u$  evaluated at two different values, say  $u_{lo}$  and  $u_{hi}$  is defined as follows:

$$\delta_i = \frac{\text{logit}^{-1}(y|u^{(hi)}, v_i, \theta) - \text{logit}^{-1}(y|u^{(lo)}, v_i, \theta)}{u^{(hi)} - u^{(lo)}}$$

where  $y$  represents the response variable,  $v_i$  the other observed inputs for individual  $i$  and  $\theta$  the vector of parameters. This average predictive comparison depends on the actual distribution of the other inputs and does not rely on an arbitrary choice of references.

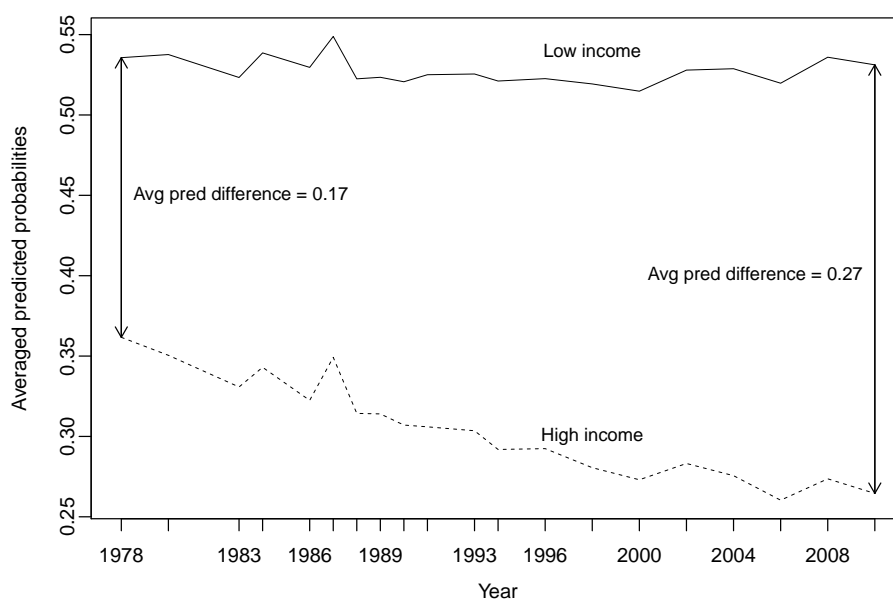
As shown in Figure 6, there is an increasing polarization of American attitudes towards redistribution between poor and rich people<sup>10</sup> and the effects of income are more pronounced over time. In fact, in the late 1970s the estimated probability of being supportive of redistribution was 0.53 for the poor and 0.36 for the rich, with an average estimated difference equal to 0.17. This rich-poor redistributive gap becomes larger in the 2000s reaching the value of 0.27 in 2010, confirming that ideological leanings in terms of redistribution have dramatically changed over the last four decades especially among rich people. Income inequality experienced in the U.S. might be a tempting explanation.

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<sup>10</sup>We defined poor and rich individuals with income one standard deviation below the mean and 2.5 standard deviation above the mean, respectively. This classification is able to capture most of the range of our data.

Typically an increase of income inequality is positively associated to support for redistribution even among the rich in the interest of minimizing societal conflicts or potential unrest. In the United States instead, although inequality has steadily increased since the 1980's, wealthy people, all things being equal, are more accepting of inequality and clearly satisfied with the *status quo*.

Figure 6: Average predictive difference in probability of being in support of redistribution over time, comparing individuals with high and low level of family income: estimated difference ranges from 0.17 in 1978 to 0.27 in 2010.



## 4.4 Education

Education has a traditional role in the economic literature on preferences: the less educated an individual is, the more he (she) will tend to favor redistribution. We found the education predictor (defined as a categorical variable) strongly related to the response variable. On average, individuals with low level of education (less than 12 years) are more in favor of redistribution by around 8% with respect to individuals with an intermediate level of education (between 12 and 16 years), while higher education (more than 16 years) does not imply a statistically different response. When we test for variation over time we have found two different time patterns: a downward trend for less educated individuals

and an upward trend for more educated, as shown in Figure 7. Net of age, cohort and other factors effects, support for redistribution increases constantly and significantly over a period of thirty years for highly educated American citizens, while less education implies a continuous and noticeable reduction of propensity towards redistribution. This pattern is even more appreciable when we look at the average predictive probability plot (Figure 8). With respect to medium educated people, in the late 1970s, being less educated translates into more than 11 percentage points in the likelihood of supporting redistribution, while being an individual with more than 16 years of education reduces the probability by 6 percentage points. In 2010 instead there is almost no difference between individuals with low and medium level of education but more educated people are more likely to support government redistributive policies by around 9 percentage points.

Figure 7: Estimates and standard errors of time-varying beta coefficients  $\hat{\beta}_t$  for different levels of education: the estimated trend effects are represented by the continuous lines. Medium educated are the reference group.

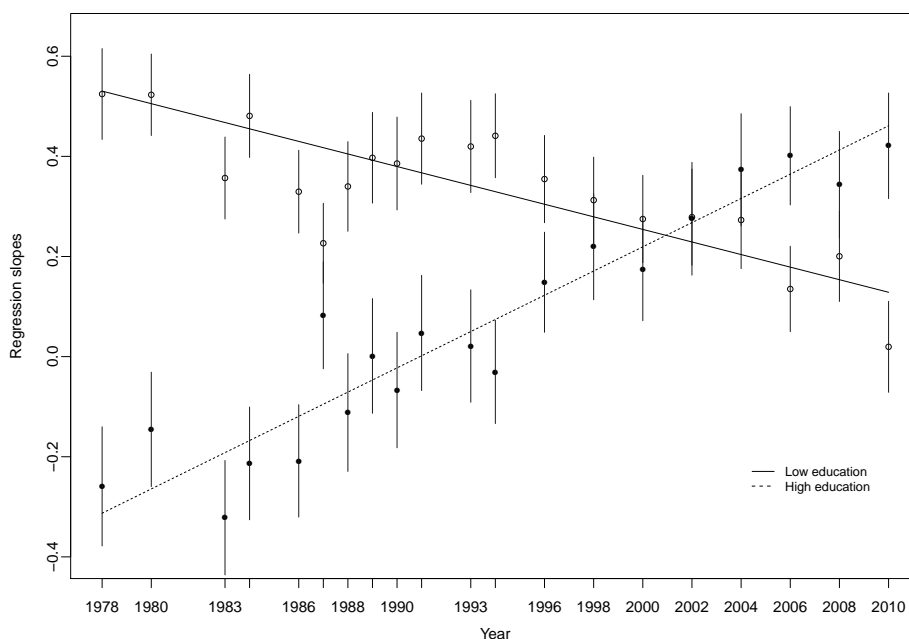
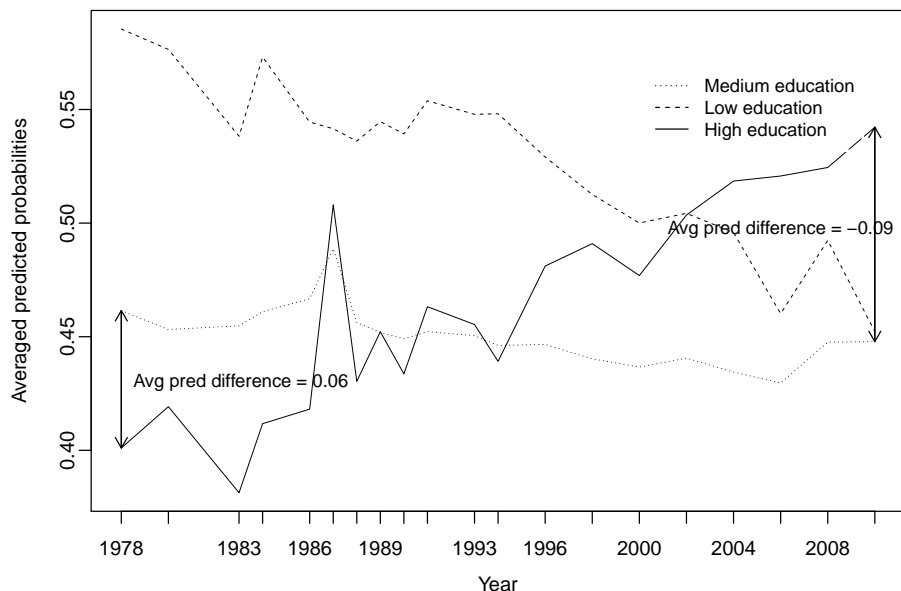


Figure 8: Average predictive difference in probability of being in support of redistribution over time among individuals with different levels of education: estimated difference between medium educated and high educated ranges from 0.06 in 1978 to -0.09 in 2010.



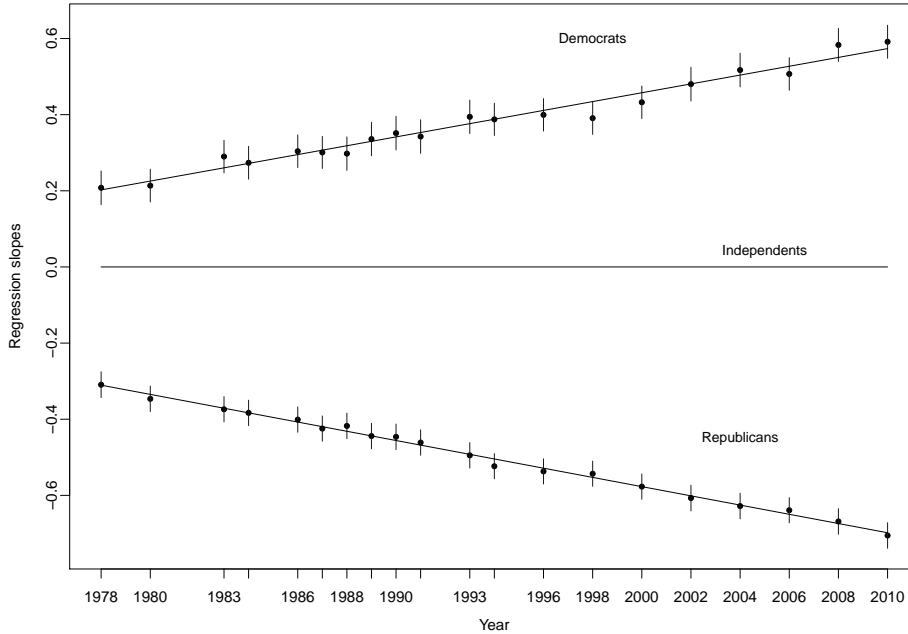
## 4.5 Political views

The self-declared position on the left-right scale works as a meaningful and highly relevant instrument that people use to frame redistributive issues. Coefficients of political views are strongly significant with the expected signs: Democrats are expected to be more in favor of redistribution than Republicans. But what is more striking is how political redistributive issues have become more strongly tied to political party identification over the past thirty years. From 1978 to 2010 Democrats and Republicans have moved apart on individual preferences towards redistribution reaching the highest level of political polarization on this issue in 2010. Figure 9 reports the estimated time-varying slope coefficients for Democratic and Republican voters. There is a sharp left-right opinion divergence: the coefficients follow quite regularly an upward linear trend for the Democrats and a downward trend for the Republicans. The evidence we presents shows that over time party affiliation becomes a stronger predictor of Americans' attitudes.

To assess more directly the attitude towards redistribution by the government among self-declared liberal and conservative voters we estimated the predictive differences in

probability of supporting redistribution (Figure 10). In 1978, the expected difference was around 12% . Since then, the gap steadily increases, peaking at 30% in 2010.

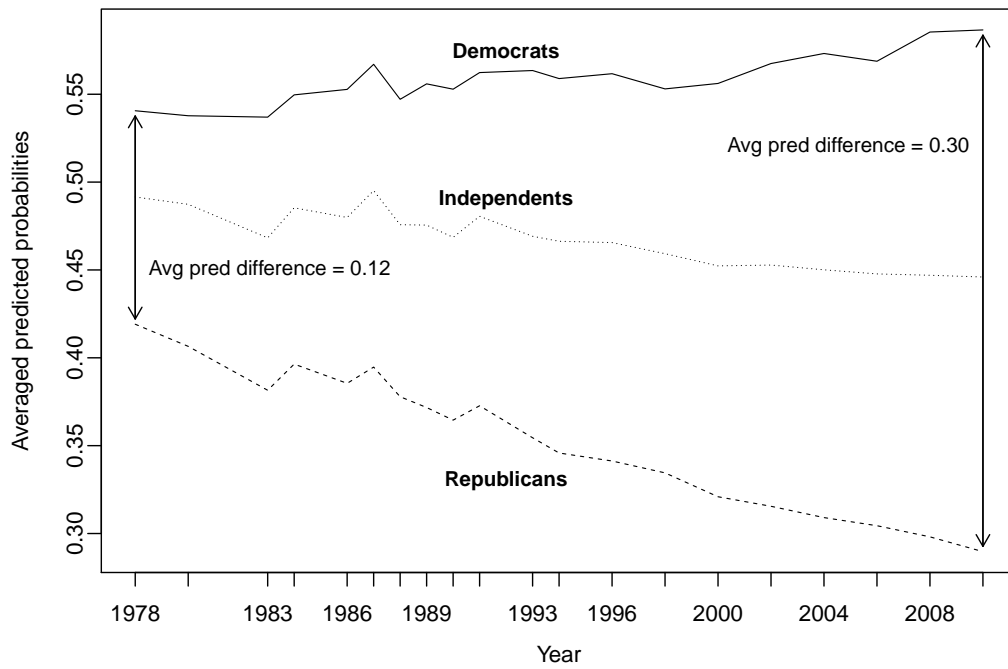
Figure 9: Estimates and standard errors of time-varying beta coefficients  $\hat{\beta}_t$  for Democrats and Republicans: the estimated trend effects are represented by the continuous lines.



## 4.6 Ethnicity

According to the literature, race is an extremely important factor in shaping preferences for redistribution. Being African-American, Hispanic, Asian or Native American is significantly associated with preferences. After controlling for cohort, income, education, religion and especially political orientation, black people and individuals belonging to non-white ethnicities are, on average over the entire time span, more supportive of redistribution than whites. However, the impact of race over attitudes fades out over time as suggested by our hierarchical model, which addresses this question by estimating the time-varying  $\beta_t$  coefficients for different ethnic groups. Figure 11 reports the  $\beta_t$  coefficients for blacks and individuals belonging to other ethnicities. Whites are the reference group. Blacks have experienced a significant downward trend in expected support for redistribution. More variation characterizes the patterns of individuals who are neither

Figure 10: Average predictive difference in probability of being in support of redistribution over time among political parties: estimated difference between Democrats and Republicans ranges from 0.12 in 1978 to 0.30 in 2010.





blacks nor whites (others): a decreasing time trend is statistically significant but estimates of the  $\beta$ 's are more spread out with relatively no negligible standard errors. This weakness is probably due to the aggregation of racial groups in the GSS survey, which for every survey year identifies only 3 groups, white/ black/ others<sup>11</sup>. Another way to see the importance of race cues is in terms of average predicted probabilities: the black-white gap steadily decreases from about 16% in the late 1970s to eventually disappear in the 2000s. Although with more fluctuations a similar pattern characterizes also the others-white gap (Figure 12).

Our analysis found unexplained variability among birth cohorts relevant only for ethnic predictors. Figure 13 reports the cohort-varying  $\beta_k$  coefficients for the different ethnic groups. The variability of  $\beta_k$  refers to underlying differences among individuals born in different cohorts. There is very little unexplained variance in cohort effect for black individuals. Conversely, a moderately large variation characterizes individuals who are neither blacks nor whites (others). The estimated standard deviation of the slopes  $\beta_k$  for this group is 0.08, which implies that cohort slopes vary significantly ranging from 0 to 0.39. Although our data does not allow us to delve much further into this pattern, we believe that this unexplained variation is large because it incorporates the effect due to the aggregation of the racial groups in GSS. A separate analysis at least for Asians and for Hispanics would presumably lead to different results.

## 4.7 Robustness of the results

We consider two forms of alternative specifications of the model to assess robustness. First, we fit the same model treating the response variable as continuous and second, changing the number of predictors categories. We compare the fits under these alternative models to assess the sensitivity of our findings to the details of the model specification. Our results hold both when the response variable is treated as continuous and when changing the number of categories. Our findings are also robust in regards to a variety of treatments of the predictors, e.g. age as continuous or categorical, education measured

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<sup>11</sup>The distinction between Hispanics and Asians is available for very few years.

Figure 11: Estimates of time-varying beta coefficients  $\hat{\beta}_t$  for ethnic groups: the estimated trend effects are represented by the continuous lines. Whites are the reference group. Standard errors are not displayed for graphical clarity.

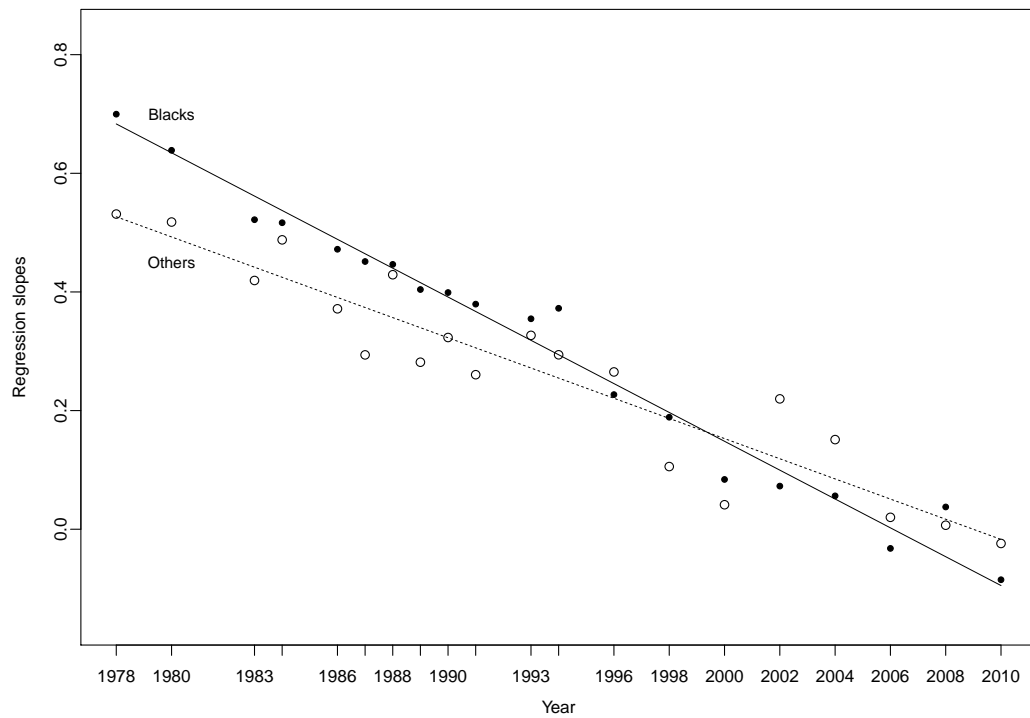


Figure 12: Average predictive difference in probability of being in support of redistribution over time, comparing individuals belonging to different ethnicities: estimated difference between blacks and whites ranges from 0.16 in 1978 to approximately zero in 2010.

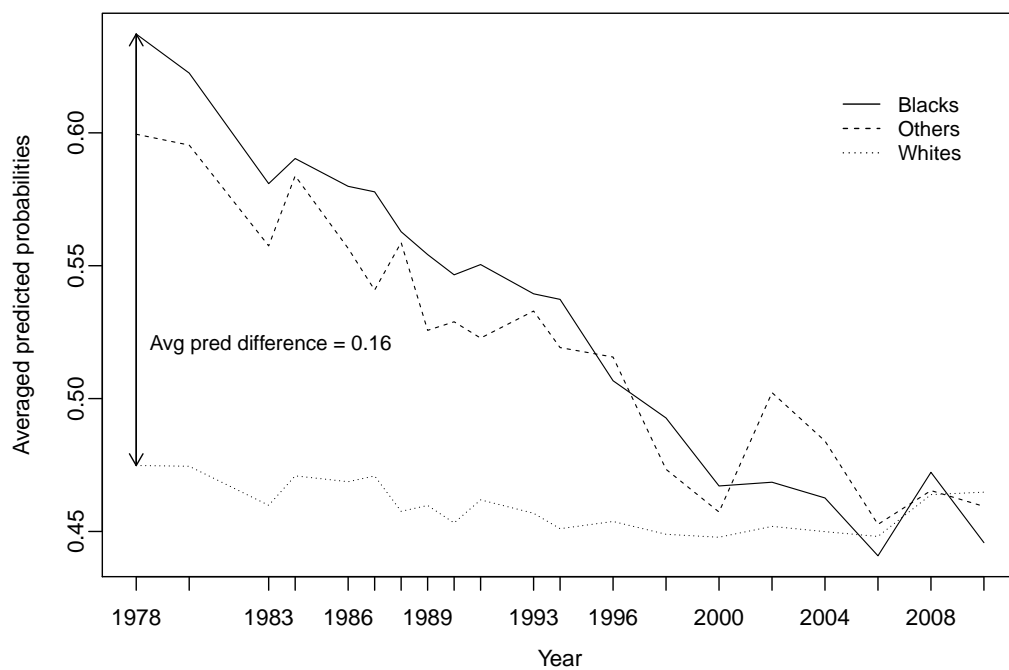
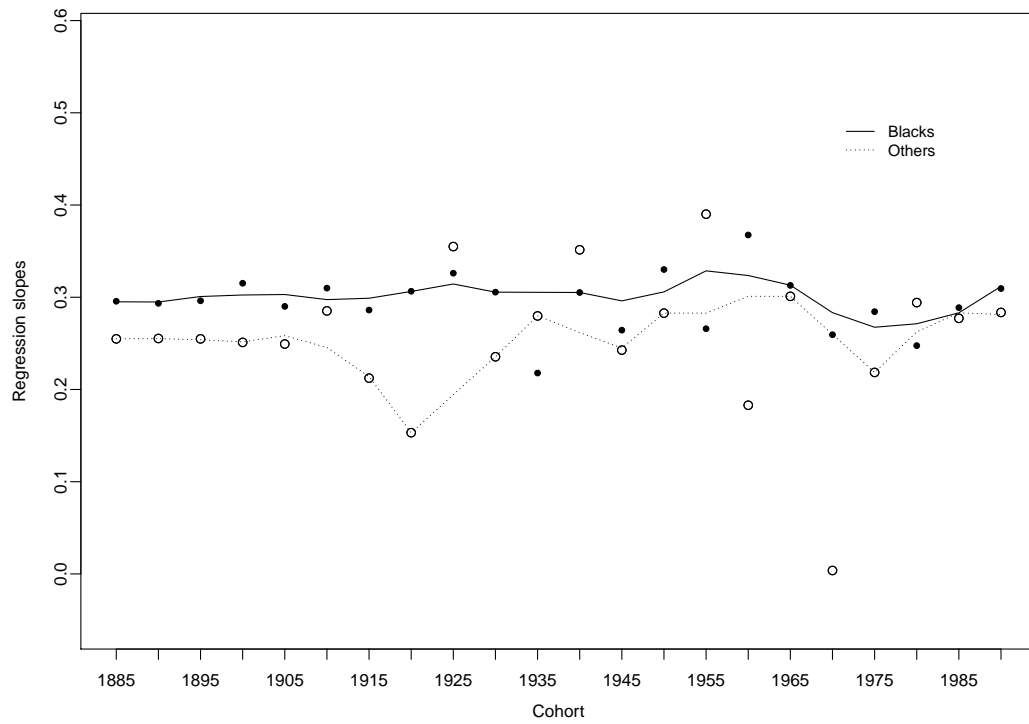


Figure 13: Estimates of cohort-varying beta coefficients  $\hat{\beta}_k$  for ethnic groups: the estimated trend effects are represented by the continuous lines. Standard errors are not displayed for graphical clarity.



as years of education or as highest qualification obtained<sup>12</sup>.

We are aware of potential endogeneity problems. Voting preferences as well as personal beliefs are intrinsically correlated with attitudes towards economic redistribution. For this reason, we fitted our model excluding individual political views as predictor. As expected, most of the effects maintain the same signs but are slightly larger in size. One important difference is related to racial issues: when we exclude self-declared political positions the influence of race on redistribution becomes significantly bigger in size. In other words, the expected difference in attitudes for redistribution between blacks and whites ranges from about 20% *versus* 16% in the late 1970s to about 6% *versus* 0% in 2010.

The question now is: how are politics and race related in mapping economic attitudes? We provide an answer to this question by fitting a model that allows for interactions between politics and ethnicity. To get a sense of what happened in the U.S. in the last thirty years we compare the average predicted probabilities of being black democratic, white democratic, black republican and white republican (Figure 14). At the beginning of the period the racial gap was larger than the political gap: for blacks being democrat or republican did not influence their redistributive attitude. Over time there is a crossover in predicted support: white or black democrats have similar attitudes and white or black republicans also tend to behave similarly.

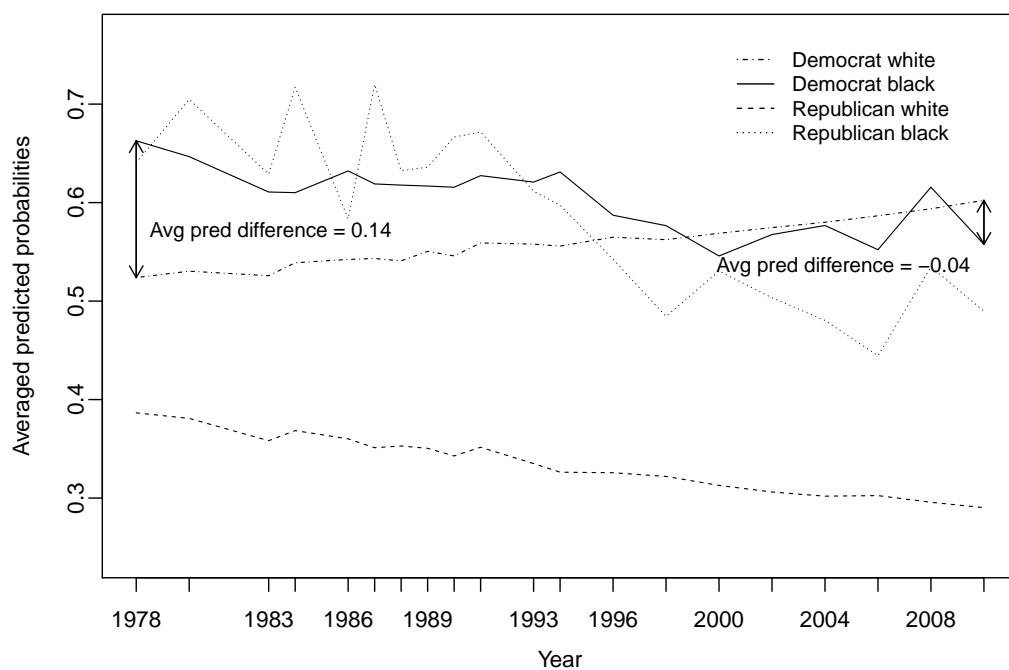
## 5 Concluding remarks

Preferences for redistribution have been traditionally investigated within a static framework. Our analysis has shown that ignoring the dynamic role of key predictors in modeling preferences for redistribution can be misleading. Cross-sectional GSS data on redistributive attitudes spanning over a period of 30 years makes it feasible to estimate a time-varying coefficient model to understand how the effects of personal characteristics have changed over time, net of individual birth cohort effect. We estimated a logistic non-nested multilevel model with three different levels of variation (individuals, time and cohort). These three different levels of variation result into covariance structure that is

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<sup>12</sup>All the different specifications of the model are available upon request.

Figure 14: Average predictive difference in probability of being in support of redistribution over time, comparing individuals belonging to different ethnicities and with different self-declared party affiliation: estimated difference between black democrats and white democrats ranges from 0.14 in 1978 to -0.04 in 2010.



complex to estimate. Our estimation procedure adopted a maximum penalized likelihood approach with a penalty term that is only weakly informative.

Despite a stable time trend in support for redistribution, our main finding is that time effect is crucial for some predictors. On the other hand, belonging to a specific cohort, to the extent that we can disentangle its effect, has a much less pronounced effect on the attitude towards redistribution. In particular, we found the following patterns:

- Personal income has a strong performance as a predictor over the whole period, but its effect increases constantly and steadily over time.
- There are two different time patterns for education: a downward trend for less-educated American citizens and an upward trend for the highest education level. University or college graduates increase their probability to be pro-redistribution constantly and significantly over time, while non-high school graduates reduce their likelihood persistently.
- Systematic differences between Democrats and Republicans have enlarged in the past thirty years. Americans are much more polarized on redistributive issues by self-declared party affiliation than they were in the past.
- Ethnicity is generally regarded as a driving factor in mapping preferences towards redistribution. Our findings however show that ethnicity matters at least until the 1990s but ethnic groups gradually move closer over time and in the 2000s ethnic gaps seem to close. In the late 1970s black individuals were 16% more likely to be in favor of redistribution compared to white individuals, whereas in the 2000s there is no significant difference. This result holds only after having controlled for political views, meaning that self-declared party identification seems to overcome ethnic group loyalty.
- Further investigation confirms that in the late 1970s the racial gap was much more important than the political gap in shaping preferences for redistribution. At the beginning of the period, for black Americans being democrat or republican did

not influence their redistributive attitudes. Over time we assist at a converge of trajectories: white or black Democrats have same attitudes as well as white or black Republicans.

Multilevel models represent a powerful framework for understanding time patterns and for modeling time-varying coefficients. A step forward in the analysis would be to include time series contextual variables, which could help explaining the time variability of the slopes.

Although our study offers strong evidence of time changing U.S. citizens' attitude towards redistribution, the GSS survey data did not allow us to follow the same individuals over time. Longitudinal data would be very helpful to confirm individual changes in the attitude of U.S. citizens in regards to economic attitudes towards government's intervention.

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