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

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ABSTRACT

This paper provides new stylized facts on how support for redistribution in the United Stated has changed over time. Since detecting structural changes in individual attitudes requires long periods of time, we used repeated cross-sectional data from the General Social Survey (GSS) cumulative Datafile that include twenty cross-sectional surveys and span a period of over thirty years (1978–2010). A multilevel logistic model with time-varying slopes and two independent levels of variation allowed us to capture temporal patterns net of age and cohort effects. Despite an overall flat trend in demand for redistribution, we find that driving factors in shaping redistributive preferences have changed considerably over time. These changes are little influenced by birth cohort. Specifically, personal income is a strong predictor, with the poor–rich gap increasing over time. Elderly people are more adverse to redistribute than they were in the past. Large changes also characterize the effects of education, ethnic bonds and self-declared party identification. Over time, highly educated people have increased their probability to be in favor of redistribution while the less educated have become less prone. Ethnicity mattered more in the 1970s than in the 2000s and it is increasingly mediated by the political party affiliation of individuals.

1. Introduction

Public support for social spending to alleviate income differences between the rich and the 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. Two main approaches have been followed in the literature to explain preferences for redistribution (Jaime-Castillo and Sáez-Lozano, 2014). One approach is based on the material utility individuals can obtain from redistributive policies and it is rooted in the median voter model (Meltzer and Richard, 1981). A second approach, not necessarily mutually exclusive, evokes the adherence to ideological principles and beliefs in supporting public welfare.

The empirical studies have provided 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; Pittau et al., 2013). These associations have been often modeled without explicitly considering temporal dynamics, creating the perception of a stationary relationship. While it seems questionable to assume the invariance of such associations over time, there has not been much work on changes of correlates over time within a single country (exceptions are, e.g.: Brooks and Manza, 2013; Georgiadis and Manning, 2012; Olivera, 2014).

This paper contributes to the existing literature by analyzing individual determinants of preferences in the United States within a chronological perspective. Since detecting structural changes in individual attitudes requires long periods of time, we used repeated cross-sectional data from the General Social Survey (GSS) cumulative Datafile that spans a reasonable long period of more than thirty years (1978–2010) and includes individuals coming from different birth cohorts. A thorough analysis of cohort versus year effects might yield insights about the belief formation and updating process. A cohort effect might support theories arguing that experiences from one's youth matter while no cohort effect might suggest a faster learning or updating process. A methodological framework based on multilevel models allows us 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 – like current income and social identity – and attitudes towards redistribution varied over time? Is it possible to detect 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 and cohort the analysis reveals that in the U.S., despite a near flat trend in the overall demand for

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redistribution, the role of some individual predictors has changed over time and both empirical findings and conclusions partially depend on which time-window is chosen for the analysis. These changes however are little influenced by birth cohort.

The rest of the paper is organized as follows. Section 2 briefly illustrates the theoretical framework for understanding why individuals would support or not public welfare. Section 3 describes the attitudes towards government redistribution in the U.S. and the individual characteristics that, according to the theoretical literature, are expected to be strong predictors of demand for redistribution. Section 4 discusses the representation, interpretation and estimation of multilevel models and the empirical strategy employed in the process. Section 5 reports the main empirical results. Section 6 summarizes and concludes.

2. Related literature

As stated in the Introduction section, a first strand of literature considers economic self-interest as 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 (Benabou and Ok, 2001; Milanovic, 2000; Ravallion and Lokshin, 2000). 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 (Cusak et al., 2006): risk of unemployment and potential devaluation of workers' skills. More generally, disadvantaged groups in the labor market, typically women, unemployed and the less educated, are, ceteris paribus, more likely to support redistribution because they hold more precarious positions.

The second broad approach states that different attitudes towards redistribution reflect polarization spread across a broad set of beliefs that is embedded within a general and coherent system of political orientation and ideological preferences (Feldman and Zaller, 1992). Beliefs in regard to the causes of inequality, concerns 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 (Alesina and La Ferrara, 2005; Alesina et al., 2012; Benabou and Tirole, 2006; Di Gioacchino et al., 2014; Fong, 2001). According to this approach people may be against or in favor of redistribution even though this hurts them materially. Such explanations come in two distinct varieties that are difficult to tease apart in observational studies: social preferences models and expressive utility models (Kamenica and Egan Brad, 2014). The first class of models specifies the extent to which an individual cares about whether the *actual* redistribution matches her ideological preferences (Costa-i-Font and Cowell, 2015; Klor and Shayo, 2010). In the second class of models, instead, an individual gets her utility from the act of declaring support or aversion to welfare assistance, since it might substantiate social identity by "signaling" conformity with group defining norms (Hillman, 2010).

Whatever theoretical framework is considered, predetermined identification like ethnicity and gender and discretionary social identity like political party affiliation, as well religious convictions or perceived social status are thought to contribute significantly in shaping people's preferences, controlling for measures of economic self-interest.

Alesina and Glaeser (2004) state that individuals who belong to one ethnic group are less willing to support redistributive programs that are perceived to benefit other ethnic groups. Lüttmer (2001) finds significance evidence of ethnic group loyalty in the U.S., that is individuals are more supportive when the share of local recipients belonging to their own ethnic group rises.

Religion traditionally influences people's beliefs about fairness, generosity, social justice, and the legitimization of welfare programs, leading to more support for redistribution (Chang, 2010). Scheve and Stasavage (2006) argue instead that religion and social spending are viewed as substitute mechanisms that insure individuals against adverse economic events, like unemployment or shocks to income. Therefore 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. Elgin et al. (2013) motivate less demand for government services by religious individuals as a form of substitution between charitable activities and government spending.

Personal beliefs – like efficiency versus reduction of inequality or luck versus effort – are also oriented by political party affiliation (Jæger, 2006). In the United States, Democrats are typically associated with the promotion of welfare policies which reduce inequality, while Republicans are associated with greater efficiencies provided by more conservative policies. However, it is still an open question whether Democratic voters are more willing to sacrifice efficiency – and even their own income – to reduce inequality (Fisman et al., 2014).

Combination of these multidimensional social identities delimits different social categories characterized by well-established behaviors and social norms. Deviation from the prescription of adopted norms (Chen and Li, 2009) can cause disutility that does not stem directly from material interests.

3. 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. Overall we could exploit twenty cross-sectional surveys, using all the data available from 1978, year in which the same question on redistribution was introduced, to 2010, spanning a period of 32 years.[1]

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 us 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. EQWLTH is the conventional variable used in the literature of redistribution since it captures in the most general terms the idea of redistributing from the rich to the poor along the entire income ladder (Alesina and La Ferrara, 2005). The role of the central government in reducing income differences is also clear. Nevertheless, a degree of ambiguity of the question remains since some respondents might object to the level at which redistributive policies ought to be enacted (central governments versus federal states), or to the specific examples of fiscal policy instruments which are given. As pointed out by a reviewer, more nuanced appreciation of these inaccuracies in the phasing of the question might be more prominent among highly educated respondents.

[1] The use of GSS data guarantees the longest time span and the largest number of surveys than any other survey in the United States. A drawback is that GSS does not allow straightforward international comparison, for which multi-country surveys like the International Social Survey Programme (ISSP) and the World Value Survey are more suitable.

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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	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 the government should reduce difference in income levels and 0 otherwise.[2] 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. Fig. 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 to adequately account 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 and are available for the whole period.[3] The selected individual predictors include: equivalent income, defined as total family income before taxes, from all sources, of the year previous to the interview, that is size-adjusted using the Luxembourg Income Study (LIS) equivalence scale[4]; age (reported in single years at last birthday); gender; marital status; ethnicity (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).

4. Modeling individual preferences over time

4.1. 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 estimate 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

[2] The choice of dichotomizing the outcome variable (EQWLTH) is only motivated by the willingness to simplify the interpretation of the results, without loosing too much of information. Some robustness exercises were carried out to check if the choice of using a binary variable did not change the main findings of the analysis (see Section 5.7).

[3] GSS Data Explorer (https://gssdataexplorer.norc.org/) is a useful tool to access and preliminary analyze GSS data.

[4] 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 lower bounds vary over time. We consider midpoints of each category 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.

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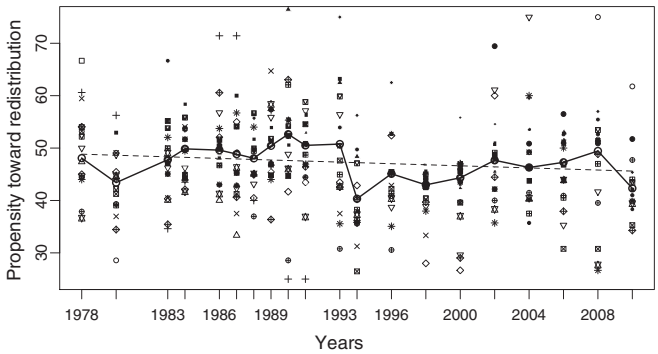

Fig. 1. Pattern of propensity towards redistribution in the U.S.: 1978–2010. Propensity towards redistribution is calculated as the percentage of respondents that agree with the statement that Government should reduce income differences. *Source*: authors' calculation on weighted data from GSS. The solid line represents national average. The dotted line represents the estimated linear trend. Different symbols represent different cohorts in each year of the interview.

(MLM), 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.[5] 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 (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:

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

where $logit^{-1}(z) = \frac{1}{1+e^{-z}}$ 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 subscripts $t[i]$ 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:

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

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

$$\begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} \sim \mathrm{MN}\left(\begin{pmatrix} f_0(t) \\ f_1(t) \end{pmatrix}, \Sigma\right), \quad \text{for} \quad t = 1, \ldots, T \tag{3}$$

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

where *MN* is a multi-normal distribution. The α_t coefficients include a polynomial trend to capture the fluctuations of the demand for redistribution during the period under study, while the polynomial trend included in the β_t coefficients intends to capture possible changes in the association between the outcome and the predictor(s) over time to the extent supported by the data. Σ represents the covariance matrix for the random time-varying intercepts and slopes, while Ω 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 un-modeled coefficients:

$$\pi_i \sim logit^{-1}\left(X_i^0 B^0 + X_i B_{t[i],k[i]}\right), \quad \text{for} \quad i = 1, \ldots, n$$

$$B_{t,k} = B_0 + B_t + B_k$$

$$B_t \sim \mathrm{MN}(f(t), \Sigma) \quad \text{for} \quad t = 1, \ldots, T$$

$$B_k \sim \mathrm{MN}(0, \Omega), \quad \text{for} \quad k = 1, \ldots, K,$$

where X^0 is the $n \times R$ matrix of individual predictors, B^0 the R-vector of their un-modeled regression coefficients; and 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, which is assumed to vary over time around a not necessarily linear trend, and B_k, along with the group-level intercepts B_0. Σ and Ω are the covariance matrices for the random coefficients.

4.2. Estimation strategy

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).

When estimating the parameters in a generalized linear mixed effects model (GLMM), it is well known that the exact likelihood function is hard to compute. Accordingly, we adopted the penalized quasi-likelihood (PQL) by Breslow and Clayton (1993), which is the most popular approximation for GLMM. 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

[5] 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. Attanasio, 1998; Deaton and Paxon, 1994; Mason and Fienberg, 1985).

covariance structures. Therefore, in order to regularize the covariance matrix, say Ψ, away from its boundary $|\Psi| = 0$,[6] we followed an approach recently suggested by Chung et al. (2013). In multivariate cases, Chung et al. recommend adding as penalty term in the penalized log-likelihood function the log-Wishart on the covariance matrix Ψ, 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 Ψ and the estimates can be viewed as posterior *modal* estimates. The Wishart prior is weakly informative, in the sense that the log-likelihood at the 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., 2013).[7] Our estimation approach is computationally convenient. However, approaches based on PQL naturally provide some shrinkage of the coefficients, and estimates are therefore less variable but slightly biased. Bias might be substantial in the presence of large variance components. To assess it, we compared the results from our core model with those obtained through a formal maximization of the marginal likelihood. Integration was performed through Markov-Chain-Monte-Carlo, and it was much more time consuming than PQL.[8] The maximal difference between parameter estimates obtained with the two methods was 0.84 standard errors. Additionally, all significant variables with PQL were significant with MCMC-ML and vice versa. We conclude that PQL is not severely biased in our case.

Since the main goal of our paper was to investigate the behavior of preference determinants over time, we first identified 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 identified the random coefficients by fitting a model separately for each year and then examined the estimated coefficients of the predictors. Coefficients treated as fixed were those small in size and almost un-varying over time.

5. 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 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. We allowed the coefficients to vary over time around a general polynomial trend. The evidence suggested that the coefficients change over time in a linear fashion. The estimated coefficients associated with a possible quadratic trend were not statistically significant. Estimates of the coefficients of our (core) model are reported in Appendix A.

5.1. Unmodeled coefficients

The coefficients of some predictors did not show variability over time and for this reason they have been left unmodeled. We left unmodeled those coefficients whose size was small and their pattern over time (and over birth cohort) was almost stable. Fig. 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, religious function 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[9] 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 unemployment 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%). Religious function attendance reduces the probability of support, accordingly with Elgin et al. (2013).

5.2. 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.[10]

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. Fig. 3 shows the estimated time effects ($\hat{\beta}_t^{age}$) and birth cohort effects ($\hat{\beta}_k^{age}$) for individuals aged over 65 net of all other factors, time and cohort included, versus time and birth cohort respectively.

Left panel of Fig. 3 shows a pronounced negative linear trend, 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. This empirical evidence apparently contrasts the expected behavior based on the senior's narrow personal self-interest. In fact, we might expect the old to be more in favor of redistribution than the young as they are more dependent on social security and they should not have prospects of upward mobility. A tentative explanation is that old Americans could worry about redistribution when they think it comes at their expenses, especially by cutting medical assistance, like Medicare and Medicaid. A different picture is captured by the right panel of the figure: attitudes towards redistribution among senior respondents 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

[6] Note that in our model there are two covariance matrices, Σ and Ω.

[7] We used the bglmer 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.

[8] Alternatively we could use the adaptive Gaussian quadrature to accurately compute the integrals, as proposed by Rabe-Hesketha et al. (2005) although in estimating our model we found MCMC computationally more convenient. However Rabe-Hesketha et al. (2005, p. 320–321) claim that results of MCMC (as here implemented) and adaptive Gaussian quadrature are exactly the same provided two conditions: the first one is that priors are vague, and the second one is that MCMC converges. We have carefully checked both conditions. Hence the results we show are indistinguishable from those that could be obtained with adaptive Gaussian quadrature.

[9] 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).

[10] Our findings are robust to alternative specification of the variable, also when allowing for concavity introducing age and age squared.

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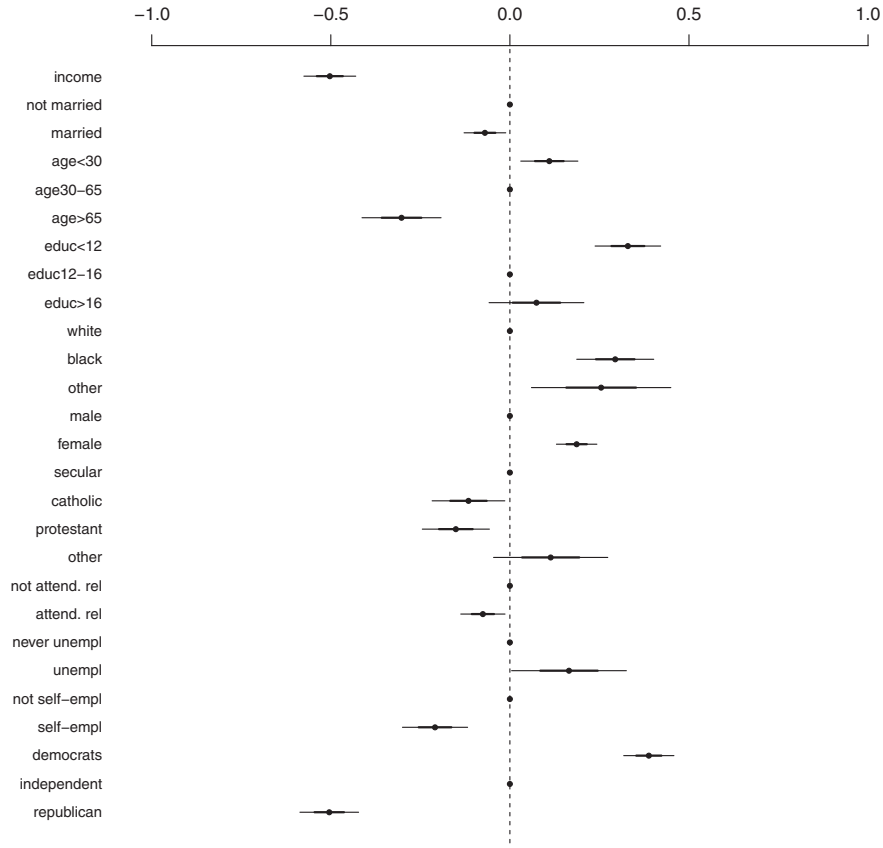

Fig. 2. Estimated coefficients with relative ± 2 standard errors of individual characteristics in the U.S. 1978–2010: varying-intercept and varying-slope multilevel logistic regression. Dependent variable: Government should reduce differences in income levels. Respondents are nested within periods and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

evidence of a plausible linear cohort effect. It should be noted that the estimated effects for the last cohorts are complete pooling estimates since people born after 1946 cannot be classified as old.

5.3. Income

We have already learned from Fig. 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 the effect of income on attitudes towards redistribution changes 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. Fig. 4 (left panel) reports the time pattern of income slopes $\hat{\beta}_t^{\text{income}}$ $(t = 1978, \cdots, 2010)$ 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. Put in another way, the shift of individual preferences

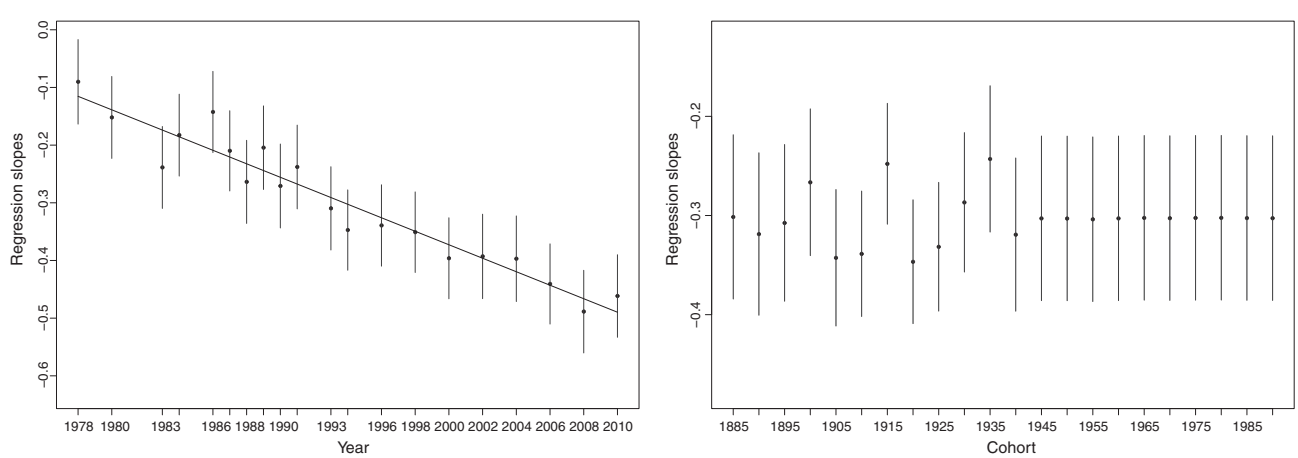

Fig. 3. Left panel: estimates and standard errors of time-varying beta coefficients $\hat{\beta}_t$ for individuals aged 65 and over, along with the estimated multilevel regression line $\beta_t^{\text{age}} = b_0 + b_1 t$. Right panel: estimates and standard errors of birth cohort-varying beta coefficients $\hat{\beta}_k$.

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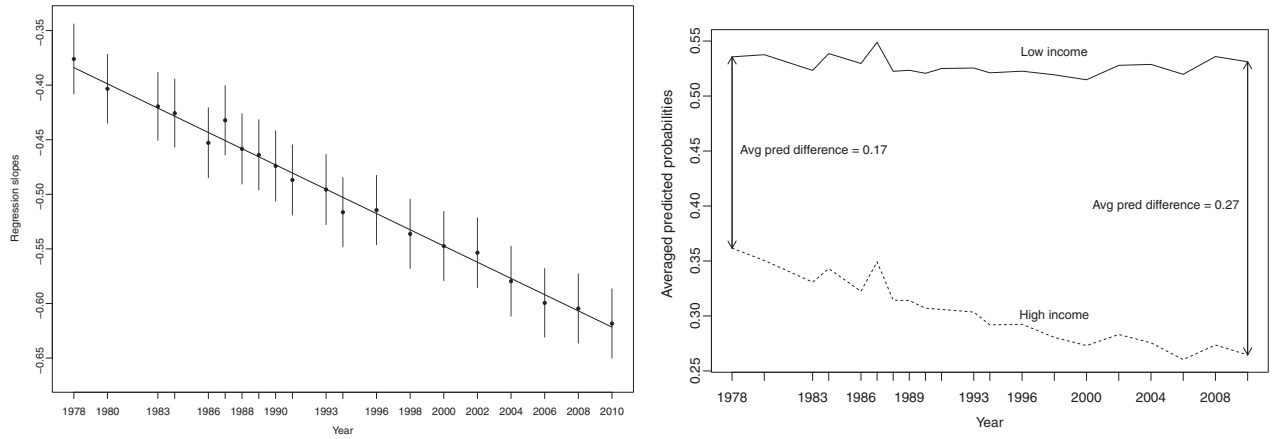

Fig. 4. Left panel: estimates and standard errors of time-varying beta coefficients $\hat{\beta}_t$ for family income; the estimated trend effect is represented by the continuous line. Right panel: average predictive difference in probability of being in support of redistribution over time, comparing individuals with high and low levels of family income: estimated difference ranges from 0.17 in 1978 to 0.27 in 2010.

on redistribution in response to changes in their personal economic circumstances is larger in the 2000s than ever in the past decades. Cohort effect is instead negligible in size.

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:

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

where y represents the response variable, v_i the other observed inputs for individual i and θ 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 Fig. 4 (right panel), there is an increasing polarization of American attitudes towards redistribution between poor and rich people.[11] 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. An increase of income inequality has been predicted to be positively associated with support for redistribution even among the rich in the interest of minimizing societal conflicts or potential unrest (Piven and Clowart, 1971). In the United States instead, although inequality has steadily increased since the 1980s, wealthy people, all things being equal, are more accepting of inequality and clearly satisfied with the status quo.

5.4. 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 tested for variation over time we found two different time patterns: a downward trend for less educated individuals and an upward trend for more educated, as shown in Fig. 5, left panel.[12] Net of age, cohort and other factor 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 (Fig. 5, right panel). 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 levels of education but more educated people are more likely to support government redistributive policies by around 9 percentage points.

5.5. Ethnicity

Ethnicity is an extremely important factor in shaping preferences over redistribution. Being African-American, Hispanic, Asian or Native American significantly affects redistributive attitude. Racial group effects have been justified in terms of social preferences. Individuals increase their support for redistribution when their group is likely to benefit from welfare spending, even if they themselves are not the recipients. However, individuals might not support their group automatically without considering consequences. Particularly, they tend to support redistribution within their group when the cost to do that is not too high (Klor and Shayo, 2010).

[11] 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.

[12] A similar pattern was found by Georgiadis and Manning (2012) in the UK.

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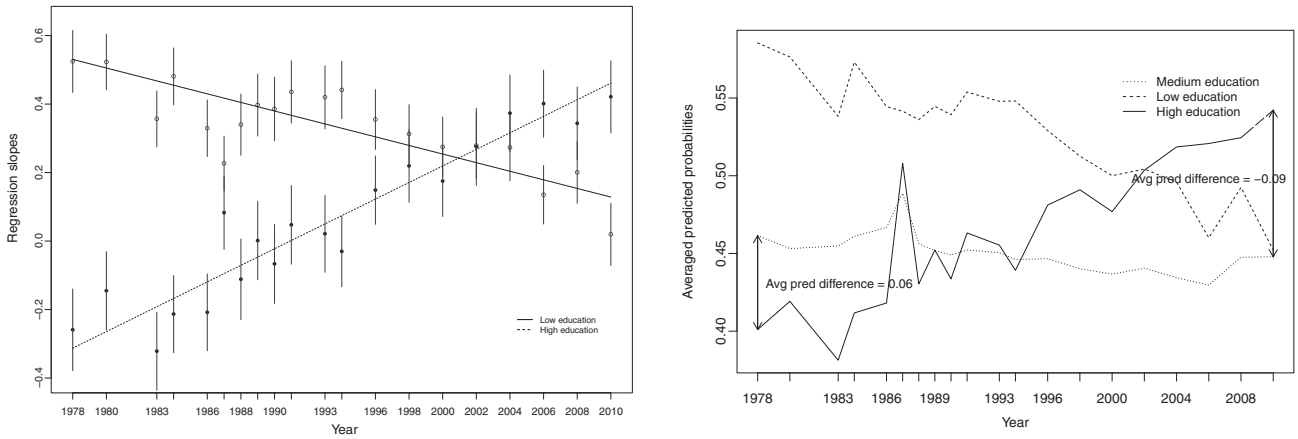

Fig. 5. Left panel: estimates and standard errors of time-varying beta coefficients $\hat{\beta}_t$ for different levels of education; the estimated trend effects are represented by the continuous lines; medium educated are the reference group. Right panel: Average predictive difference in probability 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.

After controlling for cohort, income, education, religion and especially political orientation, black people and individuals belonging to non-white ethnicity 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. Fig. 6 (left panel) reports the β_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 blacks nor whites (others): a decreasing time trend is statistically significant but estimates of the β'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 three groups, white/black/others.[13] Another way to see the importance of race 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 (Fig. 6, right panel), indicating that pre-determined identity, as racial identity is, becomes less and less important for American citizens.

5.6. Political identification

The self-declared position on the left–right scale works as a meaningful and highly relevant feature that people use to frame redistributive issues. Due to data collection mechanism and nature of the variables it is not possible to a priori exclude endogeneity problems that arise when unobserved variables affect both the outcome and independent predictors (e.g., attitude towards redistribution and political opinion). Political views as well as personal beliefs are intrinsically correlated with attitudes towards economic redistribution and potential endogeneity bias could emerge when attempting to explain 'attitudes with attitudes'. In order to minimize potential endogeneity bias in this context, we followed the practice in the literature (e.g. Bertrand and Mullainathan, 2001; Jæger, 2006) to choose a rather defined political variable (degree of adjacency to Democrats, Independent or Republicans) rather than variables with a higher level of abstraction. In this regard, political party affiliation acts as an instrument for political ideology.[14]

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 redistributive issues have become more strongly tied to political party identification over the past thirty years. From 1978 to 2010 Democratic and Republican voters have moved apart on individual preferences towards redistribution reaching the highest level of political polarization on this issue in 2010. Left panel of Fig. 7 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. Therefore, social groups defined by their partisanship responded heterogeneously when exposed to the same conditions, adopting divergent attitude patterns. 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 (Fig. 7, right panel). In 1978, the expected difference was around 12%. Since then, the gap steadily increases, peaking at 30% in 2010. Among multidimensional social identities, party affiliation, more than gender, religiosity and ethnicity, has become the most salient factor for redistributive preferences. Our empirical evidence corroborates the findings of Brooks and Manza (2013) who analyzed the period 2006–2010.

5.7. Robustness of the results and some extensions of the core model

We considered two forms of alternative specifications of the model to assess robustness. First, we fit an ordinal multilevel model treating the response variable as categorical, using all the seven categories of EQWLTH. The comparison of the results shows that there is little gain in the description and interpretation of the results.[15] Second, our findings are also robust in regard to the details of the specification of the predictors, like treating age as continuous or categorical, education measured as years of education or as highest qualification obtained, etc.

As suggested by a reviewer, we extended the model including US states as a further level of variation.[16] The most significant geographical differences are between Middle Atlantic and West South Central states. Ceteris paribus, individuals living in Middle Atlantic States are expected to be more willing to reduce income differences between the rich and the poor than individuals living in West South Central States, with an

[13] The distinction between Hispanics and Asians is available for very few years.

[14] In order to provide evidence that our final model formulation does not suffer from substantial endogeneity, we present the results of two Hausman tests. The first test shows that a model omitting the variable POLITICS as independent predictor suffers from endogeneity. The Hausman test is rejected with $p = 0.00064$. The second shows that, after including POLITICS, the Hausman test is not significant ($p = 0.859$).

[15] Results of the multilevel ordinal logit with time-varying slopes model are available upon request.

[16] Note that, in the GSS survey, given sample availability, states of residence of the respondents are grouped into nine macro-regions.

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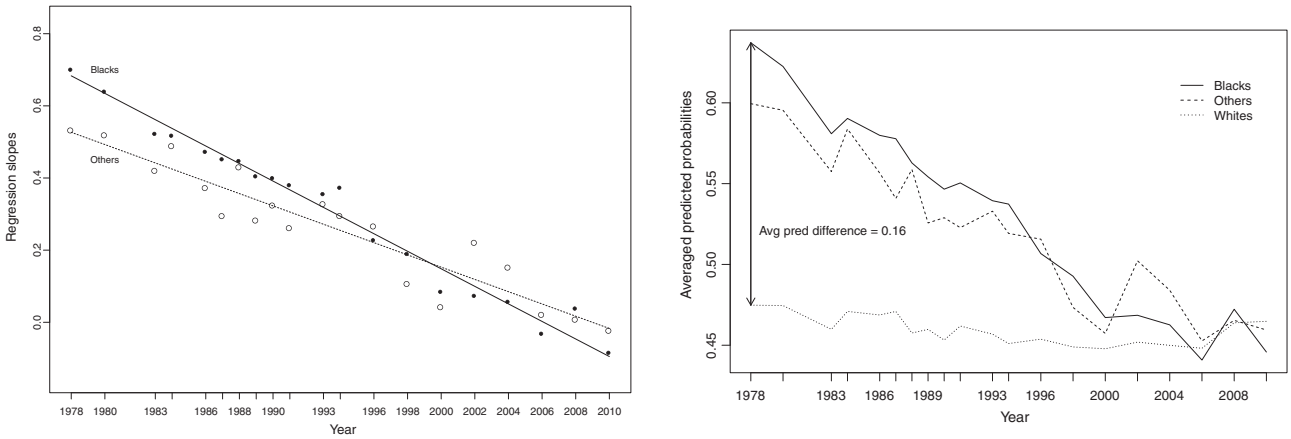

Fig. 6. Left panel: estimates of time-varying beta coefficients $\hat{\beta}_t$ for ethnic groups; the estimated trend effects are represented by the continuous lines; whites are the reference group; standard errors are not displayed for graphical clarity. Right panel: average predictive difference in 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.

expected difference in probability of being in support of redistribution of 13%. This difference does not vary significantly over time.

We also extended the core model by considering potential interactions between determinants. There is a large number of second- and higher-order interactions that may be applied to input variables and the selection procedure to keep or to exclude a particular interaction is not straightforward, but we followed this general principle (Gelman and Hill, 2007): we started considering interactions between inputs with large effects, that is effects both statistically and economically salient; we kept only those interactions that were statistically significant and with an economic relevance. This strategy does not solve all the complexities related to interactions but at least we tried not to discard potentially important pieces of information. Interestingly, interactions with the variable gender show that being female attenuates the effects of education and partisanship on preferences for redistribution. Being a low-educated female reduces by around 3% the expected probability to support redistribution with respect to a low-educated male. Instead, a female close to Republicans has an expected probability to support redistribution 6% higher than a Republican male. Corroborating evidence that the political partisanship is central in the formation of attitudes towards redistribution is given by the interaction between the variables politics and education, especially for highly educated. A highly educated Democrat increases the probability of support by 9 percentage points, while being Republican reduces it by almost 15 points. But what is most striking in terms of dynamics is how politics and ethnicity are related in mapping economic attitudes. 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 Democrat, white Democrat, black Republican and white Republican (Fig. 8). 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 and black Democrats have similar attitudes and white and black Republicans also tend to behave similarly, meaning that self-declared party identification seems to overcome ethnic group loyalty.

6. Concluding remarks

Generally, preferences for redistribution have been empirically 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. Multilevel models represent a powerful

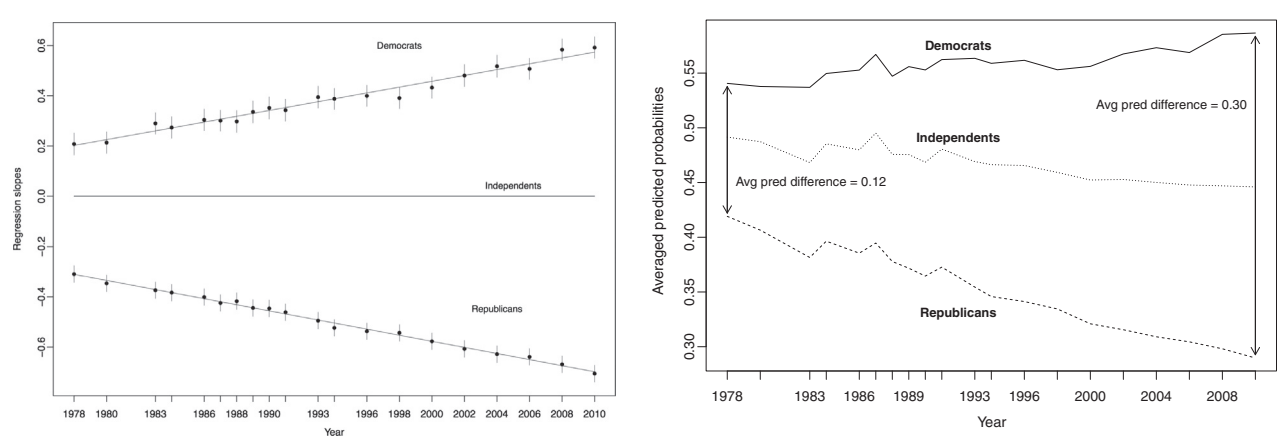

Fig. 7. Left panel: estimates and standard errors of time-varying beta coefficients $\hat{\beta}_t$ for Democrats and Republicans; the estimated trend effects are represented by the continuous lines. Right panel: average predictive difference in probability of being in support of redistribution over time among political parties; estimated difference between Democrats and Republicans ranges from 0.12 in 1978 to 0.30 in 2010.

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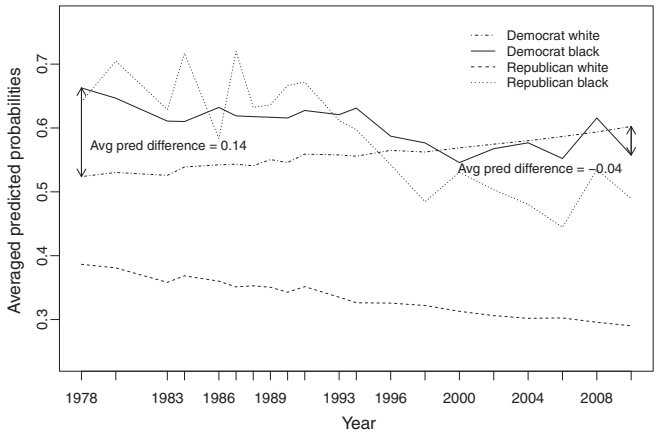

Fig. 8. Average predictive difference in probability of being in support of redistribution over time, comparing individuals belonging to different ethnicities and with different self-declared party affiliations: estimated difference between black Democrats and white Democrats ranges from 0.14 in 1978 to −0.04 in 2010.

framework for understanding time patterns of these associations. 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 a long period of time. Longitudinal data would be very helpful to confirm individual changes and to provide insights on any causal relationship. 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 a covariance structure that is complex to estimate. Our estimation procedure adopted a maximum penalized quasi-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, providing evidence that preferences for redistribution mainly changed through changes undergone by individuals, and much less through the succession of generations. We found that some specific variables play a different role over time in determining the willingness to redistribute. This represents a new empirical evidence and a novel contribution to the literature that might stimulate new theoretical debates on this topic. In particular, we found the following patterns:

- Aging influences redistributive attitudes. However, support for redistribution among older people substantially decreased in the last four decades.
- Personal income has a strong performance as a predictor over the whole period, and rich people tend to oppose redistribution more strongly 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 Democratic and Republican voters 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 group preferences gradually move closer over time and in the 2000s the gap seems to close.
- Further investigation confirms that in the late 1970s the racial gap was much more important than the political gap in shaping preferences for redistribution, but it was the reverse in the 2000s.

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Appendix A

Table A.1
Estimated coefficients with relative standard errors of the core multilevel logistic with time-varying slopes model.

	Individual predictors		Group level: period	
	Estimates	s.e.	Slope estimates	s.e.
Equivalent income	−0.503	0.036***	−0.007	0.003**
Not married	0.000	–	–	
Married	−0.070	0.029***	–	
Age <30	0.110	0.040***	0.004	0.005
Age 30–65	0.000	–	–	
Age >65	−0.303	0.055***	−0.012	0.005**
Education <12	0.329	0.046***	−0.013	0.005**
Education 12–16	0.000	–	–	
Education >16	0.074	0.066	0.024	0.006***
White	0.000	–	–	
Black	0.294	0.054***	−0.024	0.005***
Other ethnicity	0.255	0.097***	−0.017	0.009*
Male	0.000	–	–	
Female	0.186	0.028***	–	
Secular	0.000	–	–	
Catholic	−0.116	0.051**	–	
Protestant	−0.151	0.047***	–	
Other religion	0.114	0.080	–	
Not attending rel.	0.000	–	–	
Attending rel.	−0.075	0.031***	–	
Never unemployed	0.000	–	–	
Unemployment spell	0.165	0.080**	–	
Not self-employed	0.000	–	–	
Self-employed	−0.209	0.045***	–	
Democrat	0.388	0.035***	0.012	0.004***
Independent	0.000	–	–	
Republican	−0.504	0.041***	−0.012	0.005***
Year	0.006	0.004		
No. obs	23,765			
No. years	20			
No. cohorts	22			
loglik	−15,462			

Note:
*** Significance level at 0.01.
** Significance level at 0.05.
* Significance level at 0.10.

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