HOW CONSISTENT ARE PERCEPTIONS OF INEQUALITY?

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ABSTRACT. Despite recent findings in the literature that give evidence of the importance of perceived inequality in motivating social and political behavior, its analysis is still underexplored. In this paper we study whether perceptions of inequality are reflected in the individual opinions in a consistent fashion. Using the wave from the 2009 International Social Survey Program in the US, we first propose a methodology for testing the presence of inconsistencies in the perception of inequality. We then show that inconsistencies exist though they may not extend to all the domains of inequality. Inconsistency is informationally valuable because it unveils the respondents' opinions over the determinants of inequality. It therefore allows to understand what respondents think that deserves equal consideration. Yet, inconsistency is informationally valuable also for political reasons because, through equal consideration, it unveils the prevailing view of equal political treatment that respondents uphold. To confirm the relationship between equal consideration and political treatment we test and find that inconsistency is associated with a set of relevant political preferences. Our results confirm that perceived inequality motivates political behavior.

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1. INTRODUCTION

As knowledge of perceived inequality expands in depth and width, its importance becomes more apparent. A substantial literature that explores the role of inequality in motivating policies and, in general, the social and political behavior of individuals supports the view that perceptions about the degree of inequality correlate strongly, and more effectively than actual inequality, with political outcomes (Alesina and Angeletos, 2005; Ianchovichina, 2015; Gimpelson and Treisman, 2018). However, these findings and the

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evidence and narratives that reinforce the role of perceptions for policy and politics are yet not matched by an adequate knowledge of the characteristics of perceived inequality.

A question, still under explored, is whether perceptions of inequality are reflected in the individual opinions in a consistent fashion. In other words, we would expect that the opinions given by the respondents mirror their perceived inequality or, as we also say in this paper, their view of general inequality. So, if a respondent believes that society is highly unequal, her answers to the specific questions used to elicit her perceptions should always reflect her general belief. However, we show that such an expectation is naif. Inequality is a complicated and emotional concept prone to inconsistencies. The first aim that we then pursue in this paper is to introduce a test of consistency to assess whether the opinions reported by respondents match their perceived inequality. Using the 2009 wave of the ISSP (the International Social Survey Programme) data for the United States, in particular the module of Social Inequality, we test the presence of inconsistency offering, in so doing, a methodology to detect it.

Inconsistency poses a conceptual challenge to the study of perceived inequality. Why shouldn't a respondent who sees her society as highly unequal reflect in full her view in the answers that she reports? Our second aim in this paper is to shed light on this puzzle. We suggest that the respondent's perceived inequality is embedded with her view about the determinants of inequality. This information, which is disregarded in the literature, is beneficial for many reasons. First, it unveils what the respondent thinks about inequality and what she deems as bearable in an unequal distribution. It therefore allows to explore how she answers to a fundamental conceptual question in the study of inequality, namely what is to be equalized. Second, information about consistency possesses a value that can be connected to political outcomes. To explore this connection is our last goal in this paper. We combine the view of inequality that respondents report with information about their preferences over social policies. In so doing, we find further evidence of the importance of perceived inequality for political outcomes: since consistency is crucial to understand the respondent's view of inequality, it is likely to bear politically relevant consequences.

The paper is organized as follows. In the next Section we discuss how consistency helps us to reconstruct the respondent's view of inequality and affects its political importance. In Section 3 we present the empirical technique used to test for consistency. In Section 4 we introduce the data used for the empirical exercise. In Section 5 we present the paper's results. Section 6 concludes by summing up our main results.

2. The informational relevance of consistency

The analysis of perceived inequality and, in particular, the study of its determinants has a long tradition in social science (Corneo and Grüner, 2002; Alesina and La Ferrara, 2005; Kuhn, 2011; Cruces et al, 2013; Brunori, 2017; Gimpelson and Treisman, 2018).

In a recent paper, through the introduction of an empirical strategy, Bavetta et al (2018) proposed a general approach to assess how observable individual characteristics affect the joint distribution of a set of indicators of perceived inequality in specific domains. In particular, they observed that perceived inequality possesses two features that must be taken in consideration for its assessment. On the one hand, it is an essentially contested concept (Gallie, 1955). Therefore, the reconstruction of perceived inequality from the views expressed by the respondents must be done within different domains separated according to the interpretation of inequality to which the respondents subscribe because the views that they express are all equally legitimate.

On the other hand, they suggested that the joint effect of perceived inequality on the indicators may not be consistent. As far as the respondents value differently distinct aspects of the same domain, it is plausible to expect that perceived inequality may heterogeneously affect how they frame their indicators' answer. Heterogeneity calls for care in handling the analysis of perceived inequality as it introduces important, informationally rich subtleties that bear relevant political consequences.

It is the second feature that we explore in finer details in this paper, namely whether perceived inequality affects heterogeneously (inconsistently) the answers that respondents give to the questions used to elicit their perception. Recall that perceived inequality is unobservable and it is elicited from the value taken by a set of indicators that express the respondent's opinion (Bavetta et al, 2018). Note that the opinions are also shaped by the respondent's general view over society and, in particular, by how inequality or material hardship is felt, experienced or understood (Alesina et al., 2004; Luttmer and Singhal, 2011; Niehues, 2014; Corazzini et al. 2011). There is no *a priori* reason why her general perception of inequality should affect consistently the opinions expressed through the indicators because there is no univocal mechanism that allows the respondent to entangle specific dimensions (e.g., being left or right-wing, believing on the role of the state as an equalizer, etc.) in the construction of her perception. This is a relevant concern because it touches upon the identification of those aspects of inequality that deserve equal consideration according to the respondent and, ultimately, on what, in her view, grants equal political treatment (Sen, 1992; Buchanan and Congleton, 2006).

To clarify, imagine an individual who is framing her view about the path to equal educational opportunity. Imagine also that there are two ways to pursue equalization: either by paying tuition to all disadvantaged students, no matter the causes of their disadvantage; or only to students who come from under represented races to attend good schools. The opinions manifested by the respondent reflect her general view of inequality and, in particular, the importance that she attributes to the distinct dimensions (race, gender, family wealth, etc.) of the equalization process. If the respondent believes that all aspects of inequality - for example, genetic such as gender or race and social such as family wealth - matter, then what causes students' disadvantage is not relevant. In this case, her general view of inequality supports consistency in the manifestation of the opinions which, ultimately, pushes the value of the indicators homogeneously in the same direction. On the contrary, if there are inconsistencies among dimensions of inequality because the respondent attributes different importance to different dimensions - say the students' social status ought not to be equalized - then the value of the indicators are pulled in heterogeneous directions.

But then, consistency in the perception of inequality is semantically relevant because, by identifying the existence of conflicts in the role that each dimension plays in the equalization process, it sheds light on what, according to the respondent, deserves *equal consideration* (Sen, 1992). By this expression we mean what the respondent regards as important for the determination of inequality and, as such, warrants equalization. Consistency is therefore helpful to shed light on a fundamental question in the study of inequality, namely "equality of what?"If this reasoning is carried to the aggregate level, consistency contributes to crafting the prevailing view of *equal political treatment* or what, according to the respondent, would be non discriminatory governance (Buchanan and Congleton, 2006).

The literature on perceived inequality suggests that it plays a political role (Kuhn, 2011; Cruces et al, 2013; Kerr, 2014; Gimpelson and Treisman, 2018). Most likely this role extends to the circumstances of our example on equal educational opportunity. If the majority of voters believe that all aspects of inequality - genetic and social - matter, then what causes students' disadvantage is not relevant. In this case a political platform that pays tuition fees to all disadvantaged students grants equal political treatment and sports the best electoral chances. On the contrary, if there are inconsistencies in the perception of inequality because voters disagree about the aspects that deserve equal consideration, then a platform that favors under represented races only grants equal political treatment and runs the best chances to prevail. No matter the platform that would come out on top, consistency is a relevant issue for any analysis of the importance of perceived inequality and for the assessment of its impact on political outcomes.

If consistency is conceptually relevant, how can it be empirically analyzed? The assumption that we introduce in this paper recalls the idea of dominance. If a respondent's opinions are determined by a perception of higher inequality than her peers in a dimension, she is also more likely to perceive a higher inequality in another dimension, leading to univocally different responses to the indicators. This assumption is introduced formally in the next section; here we want to emphasize its consequence on the assessment of perceived inequality.

Perceived inequality is not directly observable. What we observe is a series of manifest indicators Y that capture specific dimensions (or contexts) of perceived inequality in a given domain. In the literature the indicators are either combined or taken singularly to obtain a synthetic measure that captures how individuals perceive inequality (Brunori, 2017; Jasso, 2007). No matter how the synthetic measure is constructed, a reliable assessment requires an evaluation of how general individual perceptions are.

Given a domain of perceived inequality, if respondents reveal the same propensity in reporting a specific level across dimensions, perceptions are *context-invariant*. In this case, a given respondent manifests the same propensity of positively reporting perceived inequality through indicators across contexts. Therefore, observable indicators can be seen as a direct manifestation of the unobservable perceived inequality in a domain. In this case a synthetic measure can be used in the given domain, since any Y would quite decently capture the domain's perceived inequality.

However, if the general perception is not context invariant, there is little commonality in how the respondent perceives inequality across dimensions. In this case, the general perception that a respondent has over inequality is *context-specific*. Using a single indicator or even lumping some of them together may not correctly represent the underlying perceived inequality. A more appropriate strategy would suggest to use all the available indicators as each of them captures a different individual attitude towards perceived inequality.

3. The Model

In this section we introduce the formal definition of context invariance in the perception of inequality and propose a strategy to test it.

3.1. **Context invariance: a definition.**

Let Y_{dij} denote the j-th response variable referred to the d-th domain of perceived inequality provided by individual i, with $j = 1, \dots, J_d$, $d = 1, \dots, D$ and $i = 1, \dots, N$. In our application we consider $D = 2$ domains corresponding to perceived inequality in outcome and opportunity. The Ys are based on simple questions referring to a specific context of inequality in a domain, and the answers are framed on ordered categories $l = 1, \ldots l_j$. Suppose also that $\boldsymbol{Y} = (Y_1, \ldots, Y_J)$ is the vector of observable indicators, while P_d represents the perceived inequality in a domain d (e.g., the individual latent perceived inequality of opportunity).[1]

However, P_d is not observable, thus the question is what can we learn about the distribution of $(\boldsymbol{Y}, P_d)$ when we observe only $\boldsymbol{Y}$? Let y_j indicate a potential realization of Y_j and with u and v different levels of perceived inequality with $u > v$. The hypothesis that perceptions of inequality are context invariant within a domain is described as follows:

Definition 1. (Domain Context Invariance)*: Perceived inequality is domain context-invariant if*

$$\prod_{1}^{J_d} \Pr(Y_{jd} = y_{jd} \mid P_d = u) - \Pr(Y_{jd} = y_{jd} \mid P_d = v) > 0 \qquad \forall u, v$$

In words, if perceived inequality is context-invariant, then taken two levels of perceived inequality the product of the difference in probability of reporting Y_{jd} for any two given level of perceived inequality should be positive. This suggests that individuals who appear to perceive higher inequality than their peers (since $u \neq v$) in one context are also more likely to perceive higher inequality in another context. Note that context invariance requires that the conditional distribution of Y be nondecreasing in each levels of P_d.

Given our definition of context invariance, we want to explore how to detect whether individual perceptions of inequality are general within a domain. Suppose they are not. In particular, suppose that the perception of inequality P_d is given by two different unobservable variables Q_{1d} and Q_{2d}. For example, in the case of perceived inequality of opportunity, Q_{1d} and Q_{2d} could represent perceptions of inequality related to race or gender and other features related to family background, respectively. In this framework the probability of perceiving inequality (e.g., $\Pr(Y_j = 1)$) can be described as follows:

$$\begin{aligned} Y_1 =& 1(\alpha_1 + \boldsymbol{\beta}_1 \boldsymbol{x}_i + \epsilon_1) \\ Y_2 =& 1(\alpha_2 + \boldsymbol{\beta}_2 \boldsymbol{x}_i + \epsilon_2) \end{aligned} \tag{1}$$

where $\boldsymbol{x}$ is a vector of observable characteristics, and ϵ_1 and ϵ_2 are error terms. Since Q_{1d} and Q_{2d} are not observed, one can always rewrite, say, $\epsilon_1 = \gamma_1 Q_{1d} + \delta_1 Q_{2d} + \eta_1$ and $\epsilon_2 = \gamma_2 Q_{1d} + \delta_2 Q_{2d} + \eta_2$, with η_1 and η_2 being idiosyncratic errors and γ_j and δ_j coefficient capturing how unobservables affect Y_1 and Y_2. Within this framework a simple approach to test for context invariance is to control whether ϵ_1 and ϵ_2 are residual correlated (see e.g., Bavetta *et al.*, 2018). As a matter of fact, if perceived inequality is fully context specific, then $\gamma_j = \delta_k = 0$ with $j \neq k$. In other words, conditional on $\boldsymbol{x}$, Y_1 and Y_2 would be

[1]To keep notation simple we suppress i and d from Y.

independent. While absence of no residual association may lead to conclude that perceived inequality is context-specific, finding positive (or negative) residual association does not provide any information on how general perceived inequality is, or whether it depends on multiple unobserved perceptions of inequality related to different contexts.

3.2. **Empirical strategy.** Suppose that there is a set $Q_1, \ldots, Q_K$ of context-related variables which affect the indicators Y after conditioning on $\boldsymbol{x}$. We assume that $Q_1, \ldots, Q_K$ are *discrete*, with Q_k taking say l_k levels, $k = 1, \ldots, K$. This is a fairly innocuous assumption since any continuous variable can be approximated arbitrarily well by a discrete one and it implies that we can cross-classify $Q_1, \ldots, Q_K$ into a single discrete variable that takes $l_1 \times \cdots \times l_K$ values and identifies the set of heterogeneous "types", who share similar levels of perceived inequality.

Let then $\mathcal{T} = \{1, 2, \ldots, M\}$ be the set of different unobserved types, and let T be a random variable with support in $\mathcal{T}$. Since the label of the types is arbitrary, no order is assumed on T: for example, with two binary Qs indicating high (H) or low (L) perception of inequality in a specific context, we can have four different types: (L,L), (L,H), (H,L), (H,H). In this setting, different types are simply meant to capture heterogeneous behaviors in perceiving the Ys after conditioning on $\boldsymbol{x}$, without any assumption on the underlying structure. What matters here is that a sufficient number of types is used to capture residual heterogeneity between the Ys.

How can we test for the context invariance hypothesis in the presence of a finite set of unobservable types? For the time being, consider again the analysis conditional on $\boldsymbol{x}$, and note that from Definition 1 perceived inequality is context-invariant if the conditional distribution of Y is nondecreasing. Therefore

Definition 2. (Context Invariance with Types:) *Perceived inequality is context-invariant when there is an appropriate rearrangement of the types such that*

$$\begin{gathered}\Pr(Y_1 = y_1 \mid \boldsymbol{x}, T = 1) \leq \cdots \leq \Pr(Y_1 = y_1 \mid \boldsymbol{x}, T = M) \\ \vdots \\ \Pr(Y_J = y_J \mid \boldsymbol{x}, T = 1) \leq \cdots \leq \Pr(Y_J = y_J \mid \boldsymbol{x}, T = M)\end{gathered} \tag{2}$$

with some inequality holding strictly.

Note that, if each context-related variable $Q_1, \ldots, Q_K$ is *monotonic* in $Y_1, \ldots, Y_K$, then we cannot exclude that perceived inequality is context dependent just because it is observationally equivalent to a unidimensional P_d.[2] In other words, under the assumption that the

[2]However, note that this would not necessarily be an issue since the Ys are jointly pointing to the same underlying variables.

indicators' probabilities are not monotone in each context-related variable, we can reject the context invariance hypothesis only when the inequalities in Definition 2 do not hold since, if each Q_k has not a monotone effect, then there must be at least two unobservables which pull the probabilities of how an individual reports the Ys in different directions. This observation suggests an empirical test for the context invariance of P_d when there are more than two types.

3.3. **Implementation.** Ys are usually categorical ordered indicators. Therefore the probabilities are expressed as $\Pr(Y_1 \geq y_1 \mid \boldsymbol{x}, t), \ldots \Pr(Y_J \geq y_J \mid \boldsymbol{x}, t)$, where y_j is a possible realization of Y_J. The empirical implementation of the test requires identification of these probabilities, and the possibility to estimate them in terms of the unobserved types, for each vector $\boldsymbol{x}$ describing the individual characteristics. The practical implementation of the test thus suggests the assumption that $\Pr(Y_1 \geq y_1 \mid \boldsymbol{x}, t), \ldots \Pr(Y_J \geq y_J \mid \boldsymbol{x}, t)$ are linearly additively separable in $\boldsymbol{x}$ and T, for example by assuming that:

$$
\begin{array}{rcl}
\Pr(Y_1 \geq y_1 \mid \boldsymbol{x}, t) & = & F(\alpha_1(t) + \boldsymbol{x}'\boldsymbol{\beta}_1), \\
 & \vdots & \\
\Pr(Y_J \geq y_J \mid \boldsymbol{x}, t) & = & F(\alpha_J(t) + \boldsymbol{x}'\boldsymbol{\beta}_J)
\end{array}
\tag{3}
$$

for some appropriate link function F. Under this assumption, to analyze the hypothesis of context invariance we need to estimate the individual types effects $\alpha_1(t), \ldots, \alpha_J(t)$ for $t \in \mathcal{T}$; appropriate equality and inequality restrictions on $\alpha_1(t), \ldots, \alpha_J(t)$ can then be imposed to test for the domain context invariance.

3.4. **Estimation.** To analyze how consistent are individual's PI, we need to estimate the parameters α's and β's in the nonlinear system (3), jointly with the membership probabilities $P(t)$, $t \in \mathcal{T}$. This can be accomplished by use of a semiparametric multiresponse finite mixture model. This kind of models, which have become popular in economics after Heckman and Singer 1984, decompose the observed conditional joint distribution of $Y_1, \ldots, Y_J$ into a finite number of components M with mixing probabilities $P(t)$:

$$
P(\boldsymbol{Y} \mid \boldsymbol{x}) = \sum_{t \in T} P(t) F(\alpha_1(t) + \boldsymbol{x}'\boldsymbol{\beta}_1) \cdots F(\alpha_J(t) + \boldsymbol{x}'\boldsymbol{\beta}_J).
$$

Notice that if a set of t which makes $Y_1, \ldots, Y_J$ conditional independent could be identified, then T would capture the unobservable information that compose the perception of inequality in different context. This is because knowing T would imply, say, that the knowledge of any observable variable $Y_1, \ldots, Y_{J-1}$ is irrelevant for predicting how the individual perceives inequality in Y_J, and vice versa. This form of *local independence* in the Ys states that the indicators can be considered as observable manifestations of the underlying perception of inequality.

The estimation of finite mixture models involves first a choice of an appropriate *link function* F; we use logit. Notice, however, that while we rely on the parametric choice of F for modeling each component probability, no parametric structure is imposed on T. Therefore, the system of equations (3) can be written as a system of *logit* as follows:

$$\begin{aligned} P(Y_1 \geq y_1 \mid \boldsymbol{x}, t) &= \Lambda(\alpha_1(t) + \boldsymbol{x}^{'}\boldsymbol{\beta}_1), \\ &\vdots \\ P(Y_J \geq y_J \mid \boldsymbol{x}, t) &= \Lambda(\alpha_J(t) + \boldsymbol{x}^{'}\boldsymbol{\beta}_J) \end{aligned} \tag{4}$$

where Λ is the logit link function which requires, given the ordinal nature of Y, $l_j - 1$ cut points, such that $y_j = l$ if the latent counterpart Y_j^* is $\delta_{j,l-1} \leq Y_j^* \leq \delta_{j,l}$, for $l = 1, \dots l_j$. The multiresponse finite mixture model given by the system of equations (4) is then completed by the types membership probabilities $P(t)$. To force the types probabilities to lie between zero and one and sum to one, it is convenient to use a multinomial logit parameterization:

$$P(T = t) = \frac{\exp(\alpha_T(t))}{\sum_{t=1}^{M} \exp(\alpha_T(t))}, \ \alpha_T(M) = 0 \tag{5}$$

so that the $M-1$ logit parameters α_T are reparametrization of the membership probabilities and do not impose any parametric restriction on the distribution of M estimated classes of T.

The discrete multiresponse finite mixture model is defined by equations (4)-(5), with α's and β's being the model parameters. Model (4)-(5) can be seen as an instance of a discrete multivariate MIMIC (Joreskog and Goldberger, 1975) model[3] that uses information on $\boldsymbol{x}$ and the observable joint distribution of the response variables $[Y_1, \dots, Y_J] \equiv \boldsymbol{Y}$ to learn some relevant features of the unobservable conditional distribution $P(\boldsymbol{Y} \mid \boldsymbol{x}, T)$. Contrary to the MIMIC model, the unobserved heterogeneity T is not a continuous univariate variable on the real line, but an unstructured nonparametric variable.

Estimation of the model parameters in equation (4)-(5) can be obtained by the EM algorithm, which is the standard approach for maximum likelihood estimation of finite mixture models, and has been shown (Dempster *et al.*, 1977) to converge to the maximum of the true likelihood. Given the binary nature of the response variables, the E-step is equivalent

[3]See Goodman (1974) for the seminal paper on finite mixture models with multivariate binary responses, and Huang and Bandeen-Roche (2004) for a general treatment.

to compute, for each individual, the posterior probability of belonging to each unobservable type. The M-step requires maximization of a multinomial likelihood with individual covariates, with a suitable modification to allow for linear inequality constraints.

In particular, the null hypothesis that there is an underlying context invariant unobservable variable such that $Y_1, \ldots, Y_J$ are monotonically dependent on it can be tested by setting a system of linear inequalities as explained, for example, in Bartolucci and Forcina (2005). In practice, this requires to test the hypothesis that:

$$\mathcal{H}_0: \quad \{\alpha_j(T=1) \leq \alpha_j(T=2) \leq \cdots \leq \alpha_j(T=M), \quad \forall\, j=1,\ldots,J\}. \tag{6}$$

Techniques of order restricted inference can be used to show that the Likelihood Ratio (LR) test statistic for the monotonicity null is asymptotically distributed as a mixture of chi-squared distributions.[4]

Finally, we need to determine the number of unobserved types M. The currently preferred approach suggests the use of Schwartz's Akaike and Bayesian Information Criterion (BIC) to guide this choice which, under certain conditions, is known to be consistent and helpful to prevent overparameterization.[5] BIC is calculated from the maximized log-likelihood $L(\boldsymbol{\psi})$ by penalizing parameters' proliferation, $AIC(\boldsymbol{\psi}) = -2L(\boldsymbol{\psi}) + 2v$ and $BIC(\boldsymbol{\psi}) = -2L(\boldsymbol{\psi}) + v log(n)$, where $\boldsymbol{\psi}$ is the full vector of parameters, n denotes sample size and v the number of parameters. The model with the lowest BIC is preferred. Although these criteria involve a penalty due to parameters' proliferation, we also compute a sample size adjusted BIC (sBIC) with $n = (n+2)/24$ to take into account differences in n.

4. Data

To perform the consistency test, we use the ISSP (the International Social Survey Programme) module on Social Inequality collected in 2009. The data cover a wealth of information ranging from prerequisites for success in society, to attitudes towards equality, etc. Researchers who have studied preferences and subjective values on inequality and redistribution often refer to these data (see, e.g., Corneo and Grüner, 2000; Suhrcke, 2001; Kuhn, 2011; Niehues, 2014; Brunori 2017; Gimpelson and Treisman, 2018).

Without loss of generality, we test for consistency in the United Stated of America only. Our data include 1,394 observations. Americans underestimate the level of inequality in their country (especially at the top-end of the distribution) and are less concerned than other nationals for reducing differentials at the bottom of the distribution. Such American

[4] See Gourieroux and Monfort (1995) for a general exposition and Kodde and Palm (1986) for bounds on the test distribution.

[5] See McLachlan and Peel (2004) for a thorough introduction to finite mixture models and a review of existing criteria for the choice of the number of types.

exceptionalism has indeed been the object of many studies (e.g., Alesina and Glaeser, 2004; Osberg and Smeding, 2006; Niehues, 2014).

In this paper we focus on two domains of perceived inequality: *Perceived Inequality of Outcome* and *Perceived Inequality of Opportunity*. The two domains allow us to test for consistency on both a descriptive (outcome) and a normative (opportunity) interpretation of perceived inequality, reinforcing the test's conceptual validity. The two domains are captured by multiple indicators which are described in Table 1.

TABLE 1. Indicators by domain

Domain of Perception	**Indicators**	**Description**
Inequality of Outcome	logdif	Perceived level of income differences among higher and lower professions
Inequality of Outcome	conflict	Conflicts: between people at the top of society and people at the bottom?
Inequality of Outcome	conflictr	Conflicts: between poor people and rich people?
Inequality of Outcome	conflictm	Conflicts: between management and workers?
Inequality of Opportunity	wfam	How important is coming from a wealthy family?
Inequality of Opportunity	prace	How important is a person's race?
Inequality of Opportunity	pgender	How important is a person's gender?
Inequality of Opportunity	pedu	How important is having well-educated parents?

In the pertinent ISSP Survey, most indicators in Table 1 range between 3 and 5 categories. Consider the first domain, perceived inequality of outcome. The variables *conflict*, *conflictr*, and *conflictm* correspond to as many questions that survey the respondent's opinion about the existence of conflicts among different social groups, respectively, people at the top of society and people at the bottom; poor people and rich people; management and workers. The more conflict is reported (the answers vary from "Very strong conflicts" to "No conflicts"), the more inequality we assume the respondent perceives. The last variable, *logdif*, captures individual opinions about the distribution of income. As in Jasso (2007), it is constructed from individual opinions on the earnings of specific professions. The question is: "About how much do you think a (profession) earns?", and the professions are: doctor in general practice, chairman of a large national corporation, shop assistant, unskilled worker, and cabinet minister. We identify the highest and lowest paid profession and then compute the logarithm of its ratio. We then split the individual estimated distribution in three tertiles to create an ordered variable from the lowest to the highest level of that distribution.

The indicators relative to the domain "Inequality of Opportunity" include questions on how important certain factors are for success in society: coming from a wealthy family (*wfam*), the level of parent's education (*pedu*), race (*prace*) and gender (*pgender*). The questions range from "not important at all" to "essential" but the last one, *pwork*, is reverted since it corresponds to a question about the role of effort and choice in determining achievement rather than circumstances beyond control.

Covariates are included in the analysis to reduce the level of inconsistency related to observable characteristics: gender, age (including the quadratic term), two dummies that proxy the level of education, if the individual is married, if employed, and two dummies on the reported level of income. The labels and descriptive statistics for the covariates are reported in Table 2.

TABLE 2. Summary statistics

Covariates	Mean	Std. Dev.	Description
fem	0.543		1 = female, 0 otherwise
age	4.796	1.554	individual age
age2	0.254	0.154	individual age squared
medqual	0.404		1 = intermediate level of education (“Above lowest qualifcation” or “Higher secondary completed”), 0 otherwise
highqual	0.560		1 = high level of education (“Above higher secondary level” or “University degree completed”), 0 otherwise
married	0.503		1 = married, 0 otherwise
employed	0.603		1 =employed (full time or part-time), 0 otherwise
inc2	0.339		1 = intermediate level of income (second tertile of country’s level reported incomes), 0 otherwise
inc3	0.318		1 = upper level of income (last tertile of country’s level reported incomes), 0 otherwise
Y Outcome	**Mean**	**Std. Dev.**	**Description**
conflictr	1.689	0.762	0=“There are no conflicts”, 1=“Not very strong conflicts”, 2=“Strong conflicts”, 3=“Very strong conflicts”
conflictw	1.168	0.693	0=“There are no conflicts”, 1=“Not very strong conflicts”, 2=“Strong conflicts”, 3=“Very strong conflicts”
conflictm	1.624	0.705	0=“There are no conflicts”, 1=“Not very strong conflicts”, 2=“Strong conflicts”, 3=“Very strong conflicts”
logdif3n	0.982	0.819	0=“Low perception -first tertile”, 1=“Medium perception 2=“High perception - last tertile”
Y Opportunity	**Mean**	**Std. Dev.**	**Description**
wfam	1.847	1.067	0=“Not important at all”, 1=“Not very important”, 2=“Fairly important”, 3=“Very important”, 4=“Essential”
wpar	2.399	0.870	0=“Not important at all”, 1=“Not very important”, 2=“Fairly important”, 3=“Very important”, 4=“Essential”
prace	1.000	1.002	0=“Not important at all”, 1=“Not very important”, 2=“Fairly important”, 3=“Very important”, 4=“Essential”
psex	0.997	0.991	0=“Not important at all”, 1=“Not very important”, 2=“Fairly important”, 3=“Very important”, 4=“Essential”

5. RESULTS

5.1. **Types and their view of inequality.** We start by estimating the multiresponse finite mixture model under different number of latent classes M. Table 3 reports the maximized log-likelihood and model selection criteria for the inequality of outcome and opportunity domains. A glance at Panel A and B reveals that the models with the lowest informational criteria are 4 and 5 M respectively, indicating that as many types are adequate to capture the underlying heterogeneity in the perception of inequality. The full set of parameters α, β and δ is reported in the Appendix.

TABLE 3. Model selection criteria

M	Log-Lik.	$\sharp$	BIC	sBIC	AIC
Panel A: Domain of Inequality of Outcome					
2	-4888.7105	52	10146.836	9981.6630	9881.4209
3	-4829.6780	57	10064.292	9883.2368	9773.3560
4	-4788.8736	62	10018.204	9821.2667	9701.7473
5	-4786.3629	67	10048.703	9835.8838	9706.7258
Panel B: Domain of Inequality of Opportunity					
2	-6303.6466	57	13014.524	12833.465	12721.293
3	-6226.3156	62	12895.584	12698.643	12576.631
4	-6161.8753	67	12802.426	12589.602	12457.751
5	-6134.4870	72	12783.371	12554.665	12412.974
6	-6128.6460	77	12807.411	12562.823	12411.292

Our estimates of the α parameters in equation (5) allow to calculate, by substitution, the class membership probabilities. These probabilities indicates the share of individuals from our sample that fall into each of the latent types (see Table 4). An immediate observation is that the size of these shares is quite heterogeneous, both within and across domains. The latter finding reinforces our intuition that qualitative differences between domains are understood and reported by respondents and that a proper assessment of perceived inequality must take into account the meaning that they assign to inequality.

The distribution of respondents within domains is no less revealing. The descriptive domain, inequality of outcome, displays some polarization with type 1 and 4 being the larger (more populated) groups, while in the domain inequality of opportunity there is a large group - type 4 - and multitude of smaller (in size) groups. Therefore perceptions of inequality seems to be relatively heterogeneous among Americans on how individuals perceived inequality.

Though informative, class membership probabilities are silent about who populates the different types. We can address this question using our estimates of $\widehat{\alpha}$ in Equation 4, in order

TABLE 4. Share of unobserved types

Domain	Type 1	Type 2	Type 3	Type 4	Type 5
Ineq. of Out.	0.34	0.15	0.12	0.39	-
Ineq. of Opp.	0.05	0.13	0.17	0.40	0.24

to characterize the profiles of our types in terms of the mutual association of the observed indicators Y. These profiles are reported in Table 5 (the full list of estimated coefficients is given in Table 7 and 8, in the Appendix) and represented in terms of their relationship to the indicators in each domain in Figure 1 and 2 where we depict the probability of perceiving (high) inequality in a specific context.

TABLE 5. Estimated average conditional probabilities

Indicators	Type 1	Type 2	Type 3	Type 4	Type 5
Panel A: Domain of Inequality of Outcome					
conflictr=1	0.9900	0.9963	0.9545	0.2413	-
conflictr=2	0.9973	0.8565	0.3370	0.0072	-
conflictr=3	0.9339	0.2026	0.0201	0.0003	-
conflictw=1	0.9900	0.9898	0.8060	0.0576	-
conflictw=2	0.9807	0.4151	0.0335	0.0004	-
conflictw=3	0.6793	0.0317	0.0014	0.0002	-
conflictm=1	0.9998	0.9962	0.9769	0.2569	-
conflictm=2	0.9846	0.7595	0.3512	0.0043	-
conflictm=3	0.7363	0.1270	0.0236	0.0002	-
logdif3n=1	0.4607	0.6281	0.6975	0.5366	-
logdif3n=2	0.1723	0.2959	0.3649	0.2221	-
Panel B: Domain of Inequality of Opportunity					
wfam=1	0.9954	0.9926	0.9956	0.9213	0.6586
wfam=2	0.963	0.9421	0.9643	0.5937	0.1989
wfam=3	0.7057	0.6029	0.7136	0.1241	0.0228
wfam=4	0.1353	0.0900	0.1398	0.0087	0.0014
wpar=1	0.9981	0.9953	0.9972	0.9694	0.9415
wpar=2	0.9889	0.9727	0.9833	0.8423	0.7315
wpar=3	0.9002	0.7837	0.8562	0.3564	0.2208
wpar=4	0.2374	0.1115	0.1709	0.0184	0.0094
prace=1	0.9976	0.2519	0.9581	0.8518	0.0758
prace=2	0.9649	0.0246	0.6191	0.3059	0.0057
prace=3	0.7897	0.0034	0.1980	0.0616	0.0007
prace=4	0.1336	0.0001	0.0091	0.0023	0.0002
psex=1	0.9986	0.2473	0.8969	0.8884	0.1279
psex=2	0.9755	0.0239	0.3702	0.3513	0.0103
psex=3	0.8611	0.0040	0.0979	0.0910	0.0016
psex=4	0.2291	0.0001	0.0050	0.0046	0.0001

Types' patterns closer to the diamond's border report higher perceived inequality than closer to the center. It is interesting to note from Figure 1 that, for the domain of inequality of outcome, the patterns that types follow are ordered as they do not intersect. In particular, type 1 represents individuals with the highest perceived inequality in each reported variable, while type 4 with the lowest. This suggests that, for a given type, respondents perceive inequality similarly across the board, offering evidence of consistency. Interestingly, the same similarity does not extend to the domain of inequality of opportunity. Figure 2 depicts quite a different pattern where type 2 cuts across type 4 in the variables *wfam* and *wpar*.

Combining this information on type "labeling" with the distribution of individuals across groups (Table 4), it is interesting to note that in the descriptive domain, inequality of outcome, polarization reflects extreme views over inequality of outcomes (society is very unequal - type 1 - or very equal - type 4), with smaller (in size) groups reporting a mild perception of inequality. On the contrary, the normative domain, inequality of opportunity, reveals that Americans are not particularly disturbed by inequality as share of a type that reports high perceptions (e.g., type 1 and 2) are relatively low. Interestingly, the share of - and so the probability of being of - a type that reports the lowest perception in the domain of opportunity is less than the probability of reporting a higher one, as the comparison between type 4 and 5 in the domain of opportunity illustrates.

In general, what we observe at work here is the role of equal consideration among Americans. In reporting their normative view of inequality in the American society, they disagree on the weight that ought to be attributed to genetic and social circumstances that contribute to inequality. For some Americans, in particular for type 2 respondents, genetic information contributes little to inequality, unlike social circumstances. For others, type 1, 3, 4 and 5, inequality is perceived similarly across contexts since both genetic and social circumstances contribute to its determination. To put it differently, type 2 respondents perceive inequality as largely determined by family wealth and parents' education rather than gender and race. Since the former variables only are the building blocks of inequality, type 2 respondents are most likely to say that social circumstances are the components of inequality that warrant equal consideration and that, as such, ought to be leveled off.

The evidence of inconsistency in the normative domain of perceived inequality is worth further enquiry, in two directions. First, since consistency reveals what the respondent thinks that deserves equal consideration, we want to check for robustness. Second, to better assess the political consequences of the respondent's view of inequality, we introduce information about her politically relevant preferences. We take these two directions in the same order as they have been introduced.

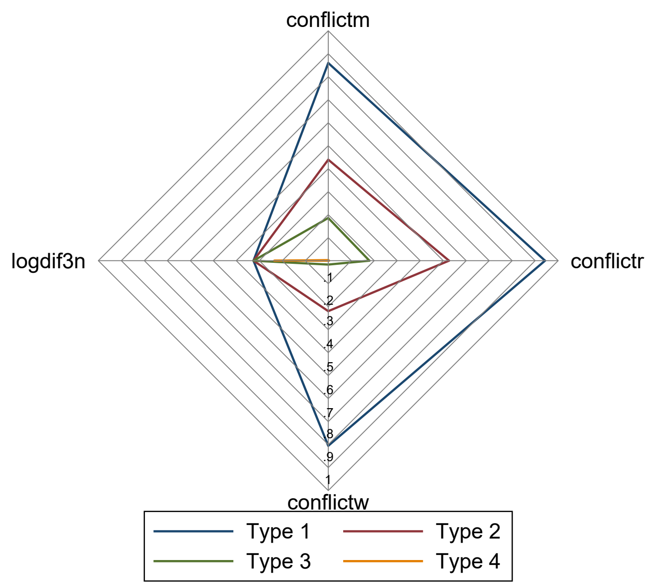

FIGURE 1. Context-related perceived inequality for the Outcome Domain

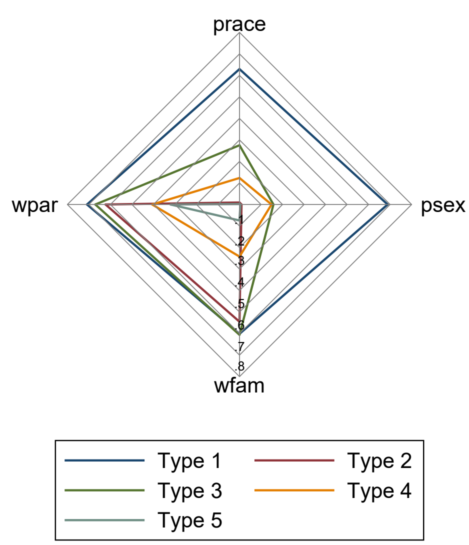

FIGURE 2. Context-related perceived inequality for the Opportunity Domain

5.2. **Testing for context invariance and robustness.** To check whether this order of types truly reflects consistency for robustness we test directly $\mathcal{H}_0$ and look at the predicted average scores of each type for the two domains of inequality under consideration. We are searching for confirmation that the pattern differences observed for the outcome and opportunity domains are not due to sample random variations but to context-specific perceptions of inequality. We therefore test the null hypothesis that perceived inequality is context invariant ($\mathcal{H}_0$). The LR test statistic for the null of context invariance is equal to 0.2457 and 105.36 for the domain of inequality of outcome and opportunity, respectively. The conservative 1% critical values with 12 and 20 d.f. (Kodde and Palm 1986, p. 1246) are equal to 32.196 and 44.646, respectively. Therefore, the hypothesis of context invariance cannot be rejected in the domain of outcome, whereas it can in the domain of inequality of opportunity.

We now further investigate this inconsistency by computing the expected scores for each Y (e.g. expected share of individuals reporting low $Y = 0, \dots J$) by types and domains. Results are reported in Figure 3 and 4 and they describe a similar picture as the average conditional probabilities. In the domain of outcome, types exhibit some kind of dominance as 1 and 4 sit above the average, reflecting the type polarization we encountered. In the domain of opportunity, type 2 predicted score crosses type 4 revealing their different general perceptions of inequality and leading, ultimately, to the inconsistency. Once again, the answer that type 2 gives to the question "equality of what?" contrasts, in this domain, with that given by the remaining types. Thus robustness confirms Americans' disagreement about the normative view of inequality and, for the purposes of this paper, the importance of a test of inconsistency in the analysis of perceived inequality.

5.3. **Perceived inequality and political preferences.** The empirical analysis conducted so far gives evidence that consistency allows to capture a relevant information about perceived inequality, namely which general views of inequality are reflected in the respondents' opinions and whether there are conflicts in society about these views. Consistency is therefore instrumental to the identification of what respondents think is relevant for the assessment of inequality or, to stick to our terminology, for equal consideration. However, consistency has more to offer to the study of perceived inequality, in particular to the assessment of its impact on political outcomes. As such an impact is gaining attention in the literature, we extend here our empirical analysis to bridge consistency and equal consideration, on the one hand, with equal political treatment, on the other.

Coherently with our previous empirical exercises, the key subject in the analysis is the type and the task is, once again, to evaluate how they differ in terms of perceived inequality.

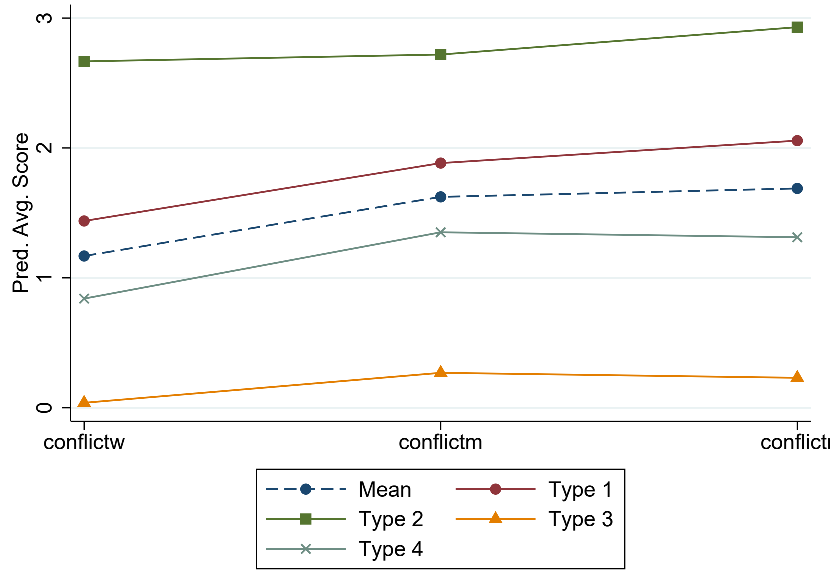

FIGURE 3. Predicted Average Scores for the Outcome Domain.

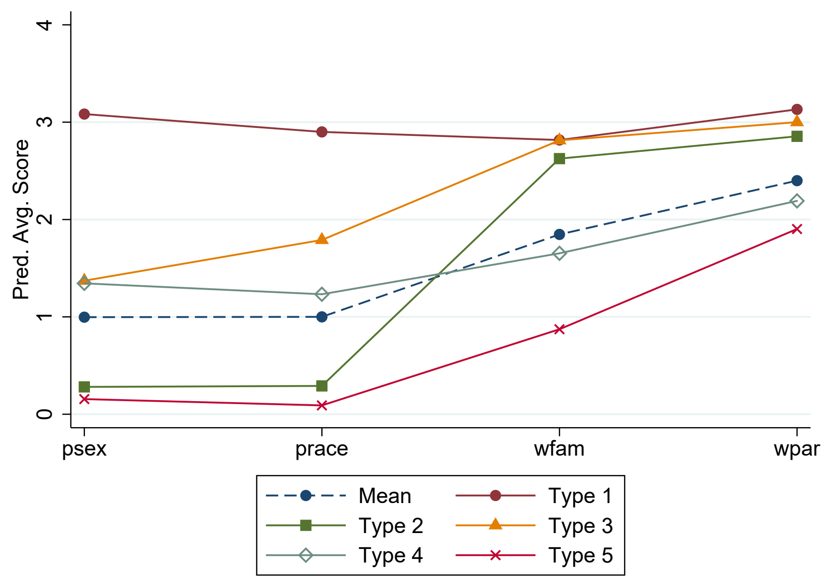

FIGURE 4. Predicted Average Scores for the Opportunity Domain.

However, to explore how these differences affect equal political treatment we study the association between the respondent's predicted perceived inequality and a set of specific questions that capture her political preferences. This is done in two steps.

In the first step we recover predicted perceived inequality types at the individual level. To assign each individuals to his (latent) perceived inequality type we use the estimated joint distribution of ($\boldsymbol{Y}$,T) to obtain an estimate of the so called posterior type probabilities. For a given pattern of the observed indicators, say $\tilde{\boldsymbol{Y}}_i = \{Y_1 = \widetilde{y}_1, \ldots, Y_J = \widetilde{y}_J\}$, and a given vector of individual characteristics $\boldsymbol{x}_i$ the probability of belonging to type t (posterior type membership probability) can be obtained by applying the Bayes rule:

$$\Pr(T_i = t|\tilde{\boldsymbol{Y}}_i, \boldsymbol{x}_i) = \frac{\Pr(T_i = t, \tilde{\boldsymbol{Y}}_i|\boldsymbol{x}_i)}{\Pr(\tilde{\boldsymbol{Y}}_i|\boldsymbol{x}_i)} \tag{7}$$

For each individual, given his vector of observed circumstances ($\tilde{\boldsymbol{Y}}_i$), T posterior probabilities are estimated, one for the membership of each type. In the literature, there are different approaches to assign individuals to types (see for a review Vermunt and Magidson, 2004). The most common way consists of a modal assignment; in practice each individual is assigned to the type for which his $\Pr(T = t|\tilde{\boldsymbol{Y}}_i)$ is the highest. However for some individuals, the highest and the second highest posterior probabilities of belonging to two different types could be particularly close i.e., if $\Pr(T = t_i|\tilde{\boldsymbol{Y}}_i) \cong \Pr(T = m_i|\tilde{\boldsymbol{Y}}_i)$ with $m, t \in \mathcal{T}$ and $m \neq t$. In such a case modal assignment can be problematic. After computing all posterior type membership probabilities using equation (7), in our example, there are no ties between the highest and the second highest type membership probabilities: the mean value of the highest individual type membership probability in sample of perceived inequality of opportunity (outcome) is of around 0.68 (0.70), with a standard deviation of 0.28 (0.25). It seems thus sensible to assign each individual to the type associated with the highest membership probability (modal assignment rule).

In the second step we estimate a standard ordered logit regression model to evaluate how predicted perceived inequality types are associated to four public policy relevant preferences. These preferences refer to the responsibility that the government ought to undertake on income distribution issues and the role that respondents think it ought to perform. To measure these four preferences we use the answers given by respondents to as many questions available in the ISSP data set. The first question probes preferences on whether people with high incomes should pay a larger share of income taxes (*Taxes*). The selectable answers, ordered on a five level scale, go from "much smaller share" to "much larger share". The second question asks whether it is the responsibility of the government to reduce income differences (*Difinc*). The third question whether the government should *not* spend less on benefits for the poor (*Poor*), while the fourth question whether the government should provide a decent standard of living for the unemployed (*Unemp*). Answers for these three questions are framed on ordered categories, ranging from "strongly disagree" to "strongly agree".

Let G_r^* be the underlying latent variable of $r = \{Taxes, Difinc, Unemp, Poor\}$, describing the underlying individual opinions in r. Thus, the regression model for each r in the two domains d that we consider is given by:

$$G_r^* = \gamma_{rd} + \sum_{t=2}^{M} \phi_{rdt} T_{di}(t) + \boldsymbol{\psi}_{rd} \boldsymbol{x}_i + \varepsilon_{rdi} \qquad \text{with } d = 1, 2. \tag{8}$$

where M is the number of estimated latent types (4 and 5 in our application), T_{di} is a dummy variable for individual type membership, ε is the random disturbance, which is assumed to follow a standardized logistic distribution; while γ, ϕ and ψ are parameters to be estimated.

Table 6 reports the estimated Average Marginal Effect (AME) and confidence interval (CI) obtained by the estimated ϕ_{dt} using an ordered logit model. AMEs measure the relative change of the latent perceived inequality on the probability that a respondent reports "much larger share" in *Taxes*, "strongly agree" in *Difinc* and *Unemp* and *Poor*. Table 6 reveals that type 1 individuals, namely respondents who report high perceived inequality, have the largest AME, compared to all other types. This is true across domains (Panel A and B) and opinions r. Interestingly, the estimated AME tend to decrease monotonically across types for inequality of outcome, while the same does not hold for inequality of opportunity.

TABLE 6. Estimated average marginal effects

Type	$Difinc$		$Unemp$		$Poor$		$Taxes$	
	AME	95% CI	AME	95% CI	AME	95% CI	AME	95% CI
Panel A: Domain of Inequality of Outcome								
1	0.179	(0.104-0.254)	0.297	(0.19-0.404)	0.261	(0.158-0.364)	0.264	(0.159-0.368)
2	0.092	(0.072-0.112)	0.101	(0.08-0.122)	0.156	(0.129-0.182)	0.197	(0.167-0.227)
3	0.056	(0.043-0.069)	0.067	(0.052-0.081)	0.114	(0.094-0.135)	0.159	(0.135-0.184)
4	0.049	(0.014-0.083)	0.048	(0.014-0.083)	0.056	(0.016-0.095)	0.109	(0.035-0.183)
Panel B: Domain of Inequality of Opportunity								
1	0.166	(0.095-0.237)	0.287	(0.185-0.388)	0.275	(0.171-0.378)	0.263	(0.163-0.363)
2	0.081	(0.055-0.107)	0.087	(0.06-0.114)	0.144	(0.103-0.184)	0.201	(0.151-0.252)
3	0.093	(0.066-0.119)	0.119	(0.088-0.151)	0.153	(0.116-0.190)	0.208	(0.161-0.254)
4	0.068	(0.052-0.084)	0.075	(0.059-0.092)	0.119	(0.097-0.141)	0.171	(0.145-0.198)
5	0.047	(0.034-0.060)	0.048	(0.035-0.061)	0.100	(0.077-0.123)	0.131	(0.104-0.159)

To better appreciate these differences in terms of consistency Figure 5 depicts the AMEs for both the inequality of outcome and opportunity domains. A quick glance reveals that consistency among types in outcome is reflected by the monotonically decreasing effect of perceived inequality types on *Taxes*, *Difinc*, *Unemp* and *Poor*. On the contrary, in the inequality of opportunity domain differences across types emerge as the AME first decreases from type 1 to type 2, then increases from type 2 to type 3 and eventually it falls back monotonically.[6] Unsurprisingly the absence of monotonicity in the AMEs' trends is related to the role played by type 2 who attributes equal consideration only to the social determinants of inequality.

The different value that type 2 respondents attribute to the determinants of inequality is reflected in a structure of preferences over distributive policies inconsistent with the other types. Type 2 respondents, for example, display almost the same marginal effect of reporting "much larger share" in *Taxes* on the general perception of inequality as type 3 respondents, despite the fact that the latter are individuals with a milder view of inequality in the American society. A reasonable interpretation of type 2 respondents' attitude toward taxing the rich is that they display an inelastic support for taxation (Ballard-Rosa et al., 2017; Kweon Kim, 2002) that is, however, not 'appropriate' to their relative view of general inequality. Similarly, type 2 respondents display a definitely higher and not appropriate marginal effect of reporting "strongly agree" in *Unemp* on the general perception of inequality as type 3 respondents, and so on for the other political preferences measured in our empirical exercise.

Most likely it is the answer that type 2 respondents give to the question "Inequality of what?" that operates here. Since they attribute equal consideration to a specific and more restricted set of determinants of inequality, the extent to which they are ready to provide political support to equalizing social policies is relatively lower than the support displayed by other types. Through their preferences, type 2 respondents lead then to a conflicting view of equal political treatment that confirms the importance of consistency in the analysis of the perception of inequality and its impact on political outcomes.

6. Conclusion

In this paper we have presented an empirical analysis that tests for consistency in the perception of inequality. Inequality is a difficult and emotional concept on which consensus is hardly available. First, it can be framed within different, equally legitimate meanings that lead to different quantitative assessments and that have different political value. though not directly related to testing for essential contestedness, our empirical exercise has indirectly

[6]For robustness we also estimated (8) including the vector of predictor posterior probabilities rather than dummies T. This is done to avoid potential issues which can derive from modal assignment. Results do not change.

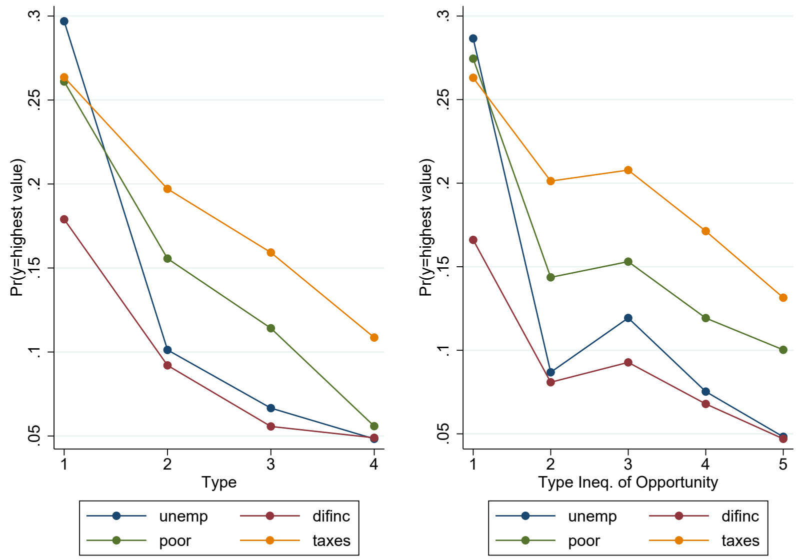

FIGURE 5. Predicted Average Marginal Effects.

confirmed the existence of alternative meanings of inequality that ought not be analytically compressed.

More importantly, our test gives evidence of inconsistencies in the respondent's perception of inequality, within domains. Such inconsistencies are associated to the determinants of inequality and, in particular, to what respondents consider acceptable in an unequal distribution. As we argued, selecting what is acceptable means choosing what ought to be given equal consideration or, in policy terms, what ought to be equalized. Consistency then yields a relevant information for both the understanding of perceived inequality and for the analysis of its political outcomes.

To reinforce the latter conclusion, we have tested how the manifested opinions and their underlying and unobserved perceived inequality are associated with some preferences for the role of government in social policy. The test has confirmed that political preferences respond to the presence of inconsistencies and that how respondents view inequality impacts on their political opinions and, ultimately, on their view of what equal political treatment consists of.

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Appendix A. Estimated Coefficients

Estimated coefficients of the discrete multiresponse finite mixture model.

Table 7. Inequality of outcome

	conflictr	conflictw	conflictm	logdif3n
$\alpha(1)$	5.847***	5.570***	7.187***	-1.301**
	(0.92)	(1.14)	(0.87)	(0.66)
$\alpha(2)$	10.007***	9.968***	10.222***	-2.067***
	(1.35)	(1.28)	(0.97)	(0.72)
$\alpha(3)$	-1.0405	-2.0676	0.4783	-1.725**
	(1.08)	(1.68)	(1.04)	(0.78)
$\alpha(4)$	3.285***	2.385**	5.374***	-0.954
	(0.88)	(0.97)	(0.84)	(0.65)
δ_2	-3.837***	-5.042***	-4.434***	-1.557***
	(0.22)	(0.45)	(0.29)	(0.07)
δ_3	-7.121***	-8.284***	-7.594***	
	(0.33)	(0.59)	(0.33)	
fem	0.468***	0.345**	0.007	-0.703***
	(0.15)	(0.16)	(0.14)	(0.11)
age	0.520	0.678*	-0.117	0.290
	(0.33)	(0.35)	(0.3)	(0.25)
$age2$	-6.038*	-7.323**	1.037	0.482
	(3.42)	(3.62)	(3.08)	(2.54)
$medqual$	-0.909*	-1.845***	-0.822*	0.058
	(0.48)	(0.61)	(0.45)	(0.37)
$highqual$	-1.353***	-2.330***	-1.103**	0.692*
	(0.48)	(0.61)	(0.45)	(0.37)
$married$	-0.284*	-0.403**	-0.170	0.315***
	(0.16)	(0.16)	(0.14)	(0.11)
$employed$	-0.448**	-0.101	-0.655***	0.335**
	(0.22)	(0.23)	(0.20)	(0.16)
$inc2$	0.332	-0.011	0.320	-0.113
	(0.23)	(0.25)	(0.21)	(0.17)
$inc3$	0.270	-0.293	0.229	0.005
	(0.26)	(0.27)	(0.23)	(0.19)

Num. of Observations = 1,217. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8. Inequality of opportunity

	wfam	wpar	prace	psex
$\alpha(1)$	6.832***	7.343***	7.999***	7.202***
	(0.87)	(0.81)	(1.04)	(1.08)
$\alpha(2)$	6.362***	6.423***	0.659	-0.8474
	(0.87)	(0.78)	(0.92)	(0.91)
$\alpha(3)$	6.871***	6.925***	5.085***	2.727***
	(0.89)	(0.81)	(0.93)	(0.87)
$\alpha(4)$	3.909***	4.516***	3.679***	2.635***
	(0.76)	(0.72)	(0.89)	(0.85)
$\alpha(5)$	2.075***	3.836***	-0.848	-1.759**
	(0.75)	(0.71)	(0.92)	(0.88)
δ_2	-2.121***	-1.790***	-2.728***	-2.921***
	(0.13)	(0.16)	(0.18)	(0.18)
δ_3	-4.534***	-4.089***	-4.761***	-4.828***
	(0.27)	(0.19)	(0.25)	(0.24)
δ_4	-7.354***	-7.499***	-8.178***	-8.162***
	(0.38)	(0.29)	(0.50)	(0.56)
fem	-0.146	0.062	0.078	0.706***
	(0.13)	(0.12)	(0.16)	(0.16)
age	0.068	0.003	-0.438	0.609*
	(0.29)	(0.27)	(0.34)	(0.33)
$age2$	-0.512	-0.570	7.608**	-2.938
	(2.95)	(2.75)	(3.49)	(3.39)
$medqual$	-1.565***	-0.563	-1.629***	-2.999***
	(0.40)	(0.36)	(0.43)	(0.43)
$highqual$	-1.507***	-0.703*	-1.540***	-2.759***
	(0.40)	(0.36)	(0.43)	(0.42)
$married$	-0.475***	-0.318**	-0.515***	-0.390**
	(0.14)	(0.13)	(0.17)	(0.16)
$employed$	0.163	0.068	0.412*	0.094
	(0.20)	(0.18)	(0.24)	(0.23)
$inc2$	0.293	-0.2436	-0.1754	-0.008
	(0.21)	(0.20)	(0.26)	(0.25)
$inc3$	0.049	-0.318	-0.269	0.015
	(0.24)	(0.22)	(0.29)	(0.28)

Num. of Observations = 1,267. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.