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AN EMPIRICAL ANALYSIS OF THE DETERMINANTS OF PERCEIVED INEQUALITY

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Perception of inequality is important for the analysis of individuals' motivations and decisions and for policy assessment. Despite the broad range of analytic gains that it grants, our knowledge about measurement and determinants of perception of inequality is still limited, since it is intrinsically unobservable, multidimensional, and essentially contested. Using a novel econometric approach, we study how observable individual characteristics affect the joint distribution of a set of indicators of perceived inequality in specific domains. Using data from the International Social Survey Programme, we shed light on the associations among these indicators and how they are affected by covariates. The approach also gives insights on some results in the literature on inequality. The role of many subjective indicators for the perception of inequality is re-examined and examples of policy applications are reviewed. The importance of our empirical approach to the measurement of perceived inequality is, in so doing, reinforced.

JEL Codes: D63, D31, D83

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1. Introduction

What motivates individuals to act depends on the environment in which they live and on its perception. Commentators agree that protesters in Tahrir Square in Cairo, in January 2011, were motivated by blatant income inequality. Yet, income inequality in Egypt was probably in decline in the years preceding the protest (Ianchovichina *et al.*, 2015). Similarly, fear of trade openness in Western countries is motivated by the perception of the effects of globalization, but it is insensitive to the empirical observations that the volume of international trade has been stagnant since the 2008 financial crisis (Manyika *et al.*, 2016). These two examples highlight the importance of the perception of inequality and, in turn, of a satisfactory analytic approach that handles effectively both its intrinsically unobservable nature and the fact that its measurement is loaded with confounding factors that make it hard to assess its extent with exactness. Recent economic literature has started to focus on perceived inequality and its determinants (e.g.

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Jasso, 2007; Cruces *et al.*, 2013; Niehues, 2014; Gimpelson and Treisman, 2015; Brunori, 2017), to overcome such difficulties. While perceived inequality is not directly observable, a number of manifest indicators can be observed. These indicators are generally available on survey data and capture individual views on the societal distribution of outcomes and opportunities as well as on their fairness. For such reasons, they have been used as "indirect" measures of the unobserved perceived inequality.

Although this practice could be an effective strategy, little has been done to provide a general framework to analyze perceived inequality. Our work goes in this direction and proposes an approach that takes into account three potential issues. First, when analyzing the literature, it emerges that the respondent and the researcher consider several interpretations of perceived inequality that are all equally legitimate. This is because perceived inequality is an essentially contested concept (Gallie, 1955). Second, even when one chooses a specific interpretation, the perception of inequality may heterogeneously affect how respondents frame their answer to the indicators. This raises an issue of multidimensionality. Third, the role of individual characteristics must be properly assessed since perceived inequality is unobservable. It follows that individual determinants can jointly affect both the latent perceived inequality and the answer to the manifest indicators.

We then propose a novel empirical approach that studies how the observable characteristics of the respondents affect the joint distribution of multiple manifest indicators of perceived inequality. More specifically, we estimate a system of equations that uses the multivariate ordered logit introduced in Dardanoni *et al.* (2016). In so doing, we are able to deal with multidimensionality and essential contestedness of the underlying unobserved perceived inequality while taking into account the role played by the individual characteristics.

A main point of this paper is to put our empirical approach to work so as to engage some of the results currently debated in the literature on inequality. We do so by offering a view on the role of many subjective variables on the perception of inequality. No less interestingly from the perspective of this paper, we also give evidence of the analytic benefits that an approach to perceived inequality that accounts for multidimensionality and essential contestedness could yield in the interpretation of social and political events.

To put our approach to work, we use data from the International Social Survey Programme's (ISSP) Social Inequality IV database. The data allow us to measure associations among observable indicators as well as the role and the effect of covariates on the associations among indicators. More precisely, for three arbitrary and yet acceptable interpretations of perceived inequality, we find evidence of the existence and importance of multidimensionality, explore cross-country differences in the level of perceived inequality, and measure how covariates affect the perception of inequality.

The paper is organized as follows. In Section 2, we introduce essential contestedness, multidimensionality, and the three domains of perceived inequality that we study ("perceived inequality of outcomes," "perceived inequality of opportunity," and "perceived unfairness"). In Section 3, we present the empirical strategy that the paper pursues. The presentation emphasizes in what sense our empirical analysis departs from the existing models. Section 4 introduces the dataset used in our empirical estimation and connects the three interpretations to the specific indicators used in the dataset. In Section 5 we discuss the results of our empirical exercise. In particular, we present the results on the associations among indicators and the confirmation of multidimensionality, first; the cross-country differences in the level of perceived inequality, in the second subsection; and the conditional survival functions of observable indicators together with their policy implications, in the last subsection. Some conclusions and suggestions for further studies bring the paper to a close.

2. The Problem of Perceived Inequality

The study of the perception of inequality is still surrounded by much difficulty because perceptions are unobservable. What we observe, instead, is a set of manifest variables/indicators which indirectly capture the respondent's views about inequality. For example, the contribution of effort for the achievement of successful economic outcomes or the view about wage differences are indicators that can be assessed through surveys that gauge the respondent's view on perceived inequality. Generally, they refer to simple questions, the answers to which are framed on ordinal categories; for instance, ranging from "strongly agree" to "strongly disagree." The value taken by any indicator depends on some observable characteristics of the respondent (gender, age, where she lives, etc.), but it also depends on the "true" level of perceived inequality that, if available, would correctly predict our manifest indicators. Pieced together, these indicators contribute to the reconstruction of the respondent's view over inequality; that is, what we call her *perception of inequality*.

Any study of the perception of inequality must then start with an effort to give analytic structure to the way in which it influences the views expressed by the respondent through the indicators. The literature has, so far, proposed two strategies: to rely on the information provided by a single indicator (Niehues, 2014; Gimpelson and Treisman, 2015), or to combine two or more indicators into a single one (Brunori, 2017; Jasso, 2007), assuming that it reflects the latent perceived inequality. In both cases, indicators are selected on the basis of their theoretical plausibility and, when more than one is plausible, evaluated by considering pairwise correlations (Kluegel and Miyano, 1995; Örkény and Székelyi, 2000; Brunori, 2017). The idea is that if a strong association between two or more indicators emerges, it might reflect the existence of common unobservable factors that capture the perception of inequality.

The two strategies are problematic because they lead to a considerable loss of information. On the one hand, most of the indicators that measure the respondent's opinions are ordinal. Therefore, simple correlations are not informative since ordinal responses may present several degrees of correlation according to the different categories. On the other hand, when multiple indicators are combined together to create a single index, pairwise or higher-order correlations are helpful to compare how reliable two indicators are as a group, but they can have limited value since correlations may disappear when observable individual characteristics are taken into account.

To deal with the complexity of perceived inequality given by its unobservable nature and the presence of multiple indicators, we propose a specific analytic structure that rests on three pillars. First, perceived inequality is *essentially contested*; namely, there are different and equally legitimate interpretations of perceived inequality that can be derived piecing together these indicators in several ways. Second, perceived inequality is *multidimensional* since, although a specific interpretation is selected among the many, still multiple "aspects" could affect how the respondent answers the several indicators that compose that specific interpretation. Third, a key role is played by *covariates* that affect both the respondent's answers for each indicator and their level of perceived inequality and give us important insights for public policy and accountability. Moreover, the determinants of perceived inequality are also crucial for public policy and accountability.

2.1. *Essential Contestedness and Domains*

The reconstruction of perceived inequality from the views expressed by the respondent may be done in different ways according to the interpretation of inequality to which the respondent subscribes. Substantive and reasonable disagreements about how to reconstruct the views originate in the evaluative nature of any assessment of inequality. In other words, the views expressed by respondents through the indicators may be reconstructed in different, equally legitimate, ways separated by non-reducible disagreements. Perceived inequality is therefore an *essentially contested concept* (Gallie, 1955).

For example, we might be interested in the respondent's perception of inequality of opportunity and piece together her answers on the relevant indicators. Or we might be concerned with the respondent's perception of unfairness and put together different indicators. Both are instances of perceived inequality the differences between which cannot be easily *a priori* settled. We must accept that many instances of an archetype "perceived inequality" exist. It is therefore legitimate to define and measure perceived inequality in different ways.

In this paper, we select three interpretations of perceived inequality because of their intuitive appeal and their relevance in the literature. The first interpretation that we propose is *perceived inequality of outcome*. It refers to views about the distribution of some monetary (e.g. income or wealth) or non-monetary (e.g. well-being or happiness) outcome. One way to assess perceived inequality of outcome is to ask for views about the gap between different social groups. Kelley and Zagorski (2004) and Osberg and Smeeding (2006) use questions about the respondents' estimates of pay for five professions (CEO, cabinet minister, lawyers, skilled, and unskilled workers) and elicit their views about distances. The theoretical justification for their approach is in Jasso (2007), where a ratio index based on views about how income is distributed among several professions is constructed to assess the difference between high- and low-paying occupations. Alternatively, Niehues (2014) and Gimpelson and Treisman (2015) use a variable from the ISSP that aggregates individual answers to form an average perception of income distribution, divided into seven income classes then represented by diagrams. On the basis of this information, they compute a subjective Gini coefficient that is, in turn, compared with the objective Gini to assess their distance and extract policy implications about preference for redistribution and taste for revolt.

An alternative reading of perceived inequality looks at the different sets of opportunities that individuals have, irrespective of the outcomes that they achieve. *Perceived inequality of opportunity* is concerned with the respondents' views about how, in their society, opportunities are evenly distributed. In general, opportunities refer to health, education, inherited wealth, social connections deemed useful for success, genetic skills, and so on. Approaching perceived inequality from the perspective of opportunity marks a substantial departure from the case of outcomes. For instance, Brunori (2017) emphasizes the role of cultural and social variables as well as of personal experiences of intergenerational social mobility to determine the respondents' perception of inequality of opportunity.

The final interpretation of perceived inequality that we propose is *perceived unfairness* which includes an assessment about whether a certain degree of inequality in a given distribution is justified. While outcomes and opportunities can be observed and described, the assessment of fairness, although close in spirit, may also depend on what the respondent thinks a person is responsible for.

2.2. *Multidimensionality*

Perceived inequality is reconstructed from the aggregation of the respondent's views manifested through one or more observable indicators. Multidimensionality arises when, for a given domain of perceived inequality, it is possible to consider more than one specific "aspect" (in different contexts, see also Amiel *et al.*, 2015; Roemer and Trannoy, 2016). For example, take the case of perceived inequality of opportunity. It is well known that perceived inequality of opportunity can refer to different aspects (e.g. education, health, etc.), although the same domain is examined. Since more than one aspect is involved, an effective strategy to empirically capture unobserved perceived inequality is to use all available singular manifest indicators. From an empirical point of view, the existence of multidimensionality also implies that the joint effect of perceived inequality on indicators may not be monotone. As far as the respondents value differently distinct aspects of the same domain of perceived inequality, it is plausible to expect that perceived inequality may heterogeneously affect how they frame their indicators' answer.

2.3. *The Determinants of Perceived Inequality*

Given contestedness and multidimensionality, the determinants of perceived inequality influence the respondent's answers to single indicators and the level of perceived inequality in a specific domain.

The determinants of perceived inequality include many factors: demographic, socioeconomic, and ideological. For example, demographic determinants suggest that women are more likely than men to perceive a distribution as unfair

(Verwiebe and Wegener, 2000; Alesina and Giuliano, 2009), that gender affects altruism (Andreoni and Vesterlund, 2001) and competition (Gneezy *et al.*, 2009), or that age is a predictor of perceived inequality because adults have more cognitive skills to process relevant information than young individuals (Cruces *et al.*, 2013).

Socioeconomic determinants are also important. For example, income is a major factor, directly and indirectly. Rich individuals perceive less inequality and are readier to accept it than poor individuals (Meltzer and Richard, 1981; Persson and Tabellini, 1994; Corneo and Grüner, 2000, 2002; Ravallion and Lokshin, 2000; Suhrcke, 2001). Cruces *et al.* (2013) find that the level of income of the reference group explains the gap between objective and perceived inequality. Income is also indirectly related to perceived inequality through expectations about future income, because the latter bear on the justification of inequality (Hirschman and Rothschild, 1973; Benabou and Ok, 2001). In particular, the poor's belief that he may move upward in the income ladder favors the approval of a certain degree of inequality not to bear the burden of future redistribution.

Finally, the value system that a respondent endorses has a substantial impact on her perception of inequality. Left-oriented respondents tend to consider distributions as unfair (Alesina *et al.*, 2004; Alesina and Giuliano, 2009), like respondents who believe in egalitarianism (Verwiebe and Wegener, 2000). The reason is that left-oriented respondents are less likely to believe that economic success is entirely the outcome of effort or, in general, of factors under the individual's control (Alesina and Glaeser, 2004; Alesina and Angeletos, 2005; Benabou and Tirole, 2006; Bavetta and Navarra, 2012). Additionally, political orientation and cultural and religious attitudes also affect how inequality is perceived (Weber, 1930; Suhrcke, 2001; Lübker, 2004; Benabou and Tirole, 2006; Alesina and Giuliano, 2009).

The analysis of the determinants of perceived inequality is important for policy purposes because how respondents perceive the level of inequality motivates their political behavior.[1] Recent events such as Brexit or the election of Donald Trump can be better interpreted with information about perceptions of inequality. Another example is the support that populist political forces are gaining among Italians. As the work shows in Section 5.2, there is evidence of a substantial difference between the level of objective inequality in Italy and its perception. The belief that personal economic outcomes cannot be attributed to factors under the control of the individual has led Italians to perceive their society as unfair and to look for the overhaul of the political establishment. Information about perceived inequality qualifies in many important ways how society works and sharpens the interpretation of the changes that it is undergoing.

Contestedness, multidimensionality, and the relevance of covariates translate into formal requirements in the next section, where we propose an empirical strategy that studies the extent and nature of the residual correlation among the indicators used to reconstruct perceived inequality.

[1]Other domains where perceived inequality is important include, without exhaustiveness, investment in education, consumption, or family choices. They are not covered by our analysis.

3. Empirical Strategy

Our aim is to study how observable individual characteristics affect the joint distribution of a set of perceived inequality's indicators in a specific domain. Let us assume that the ith individual's perceived inequality in a specific domain d (with $d=1,\ldots,D$) is measured by an unobserved (latent) variable denoted by I_i^d. Instead, one observes a set of K ordered categorical indicators Y_{ki}^d, taking $m=1,\ldots,M$ categories. These indicators can be interpreted as the manifest effect of a latent variable. In particular, it is assumed that the responses on the indicators are the result of an individual's position on the underlying latent variable. Thus if one could observe how individuals perceive inequality in a specific domain—that is, I^d—then controlling for this variable should capture all sources of systematic correlation among indicators.

To better understand the relationship between indicators and the unobserved I^d, let denote with $\widetilde{Y}_{ki}^d$ the latent counterpart to Y_{ki}^d. $\widetilde{Y}_{ki}^d$ reflects a specific aspect or view of the unobserved I_i^d according to what the indicator is pointing. Thus it provides a partial view of the more complex structure of the latent I^d. Suppose that $\widetilde{Y}_{ki}^d$ is a simple function of I_i^d and a vector of covariates $\boldsymbol{x}$. For the sake of generality, we do not impose any restriction on how $\boldsymbol{x}$ affects each indicator among domains. Moreover, how individuals perceive inequality can also be affected by $\boldsymbol{x}$ (which means that I_i^d is also a function of $\boldsymbol{x}$). This yields:

$$\begin{aligned} \widetilde{Y}_{1i}^d &= \beta_1 I_i^d(\boldsymbol{x}) + x_i'\gamma_1 + \epsilon_{1i} \\ \vdots \quad & \qquad \vdots \\ \widetilde{Y}_{Ki}^d &= \beta_K I_i^d(\boldsymbol{x}) + x_i'\gamma_K + \epsilon_{Ki} \end{aligned} \tag{1}$$

where ϵ_{ki} is a term reflecting residual reporting error. The system of equations (1) states that the attitude of individuals to report agreement with question Y_k reflects the level of unobserved perceived inequality in a domain I^d and a measurement error which is the result of observable ($\boldsymbol{x}$) and unobservable characteristics. Thus the parameters γ_k represent potential reporting heterogeneity due to differences on how individuals perceive a specific indicator in the domain d. The latent variable $\widetilde{Y}_{ki}^d$ can be linked to the categorical indicator using the following standard observation mechanism:

$$Y_{ki}=m, \text{ if } \alpha_{m-1} < \widetilde{Y}_{ki}^d \leq \alpha_m,\ m=1,\ldots,M. \tag{2}$$

Equation (2) shows that the observable indicator Y_{ki} takes the value m if the $\widetilde{Y}_{ki}^d$ lies between the two thresholds α_{m-1} and α_m. If I_i^d was directly observable, and assuming that the error terms follow a standard normal (logistic) distribution, one could combine the observation mechanism with equation (1) and estimate the model using K separate ordered probit (logit) models. However I_i^d is not directly observable, and thus the system (1) can be rewritten as follows:

$$\begin{aligned} \widetilde{Y}_{1i}^d &= \boldsymbol{x}_i'\gamma_1 + \eta_{1i} \\ \vdots \quad & \qquad \vdots \\ \widetilde{Y}_{Ki}^d &= \boldsymbol{x}_i'\gamma_K + \eta_{Ki} \end{aligned} \tag{3}$$

where γ_k describes, for a given domain d, the direct effect of $\boldsymbol{x}$ on $\widetilde{Y}^{d}_{ki}$ capturing a specific aspect of how an individual perceives inequality, while $\eta_{1i}, \ldots, \eta_{Ki}$ are correlated error terms.

The multivariate system of equations (3) has some relevant features. First, jointly modeling the distribution of $Y^d_1, \ldots, Y^d_k$ allows us to use all the available information gathered by the vector of indicators $\boldsymbol{Y}^d$. This provides a richer design than using one Y^d_k or a composite indicator of $Y^d_1, \ldots, Y^d_k$.

Second, all equations in (3) can be estimated separately as single ordered probit (logit) models, but the estimated coefficients would be inefficient because the correlation between the error terms is neglected. Indeed, the system (3) models directly the residual association between indicators, after conditioning for observable covariates, and it is better suited to evaluate whether indicators are jointly measuring the same unobserved domain. In particular, since I^d_i is not observed, one can always rewrite, say, $\eta_{ki}=\beta_k I^d_i(\boldsymbol{x})+\epsilon_{ki}$ and $\eta_{ji}=\beta_j I^d_i(\boldsymbol{x})+\epsilon_{ji}$ (with $k,j=1,\ldots,K$ and $j \neq k$), where ϵ_{ki} and ϵ_{ji} are idiosyncratic error terms, while β_k and β_j measure how η_{ki} and η_{ji} are associated. Indeed, if two indicators, say Y^d_k and Y^d_j, are not related to each other through I^d, then they would be independent, since the conditional residual association between η_{ki} and η_{ji} is zero. The null hypothesis of no residual association between Y^d_k and Y^d_j amounts to test that the association between η_{ji} and η_{ki} is zero. In practice, the estimated pairwise associations measure how far unobserved factors related to I^d simultaneously influence the perception of $\boldsymbol{Y}^d$.

3.1. *Empirical Specification and Hypotheses of Interest*

To study the joint distribution of the observable indicators $Y^d_1, \ldots, Y^d_K$ for each domain, we rely on the multivariate ordered logit model. This model jointly estimates a set of equations, one for each indicator, that are jointly related through a set of parameters that capture residual unobserved heterogeneity. Details on this model are reported in Appendix A (in the Online Supporting Information—for a more general discussion of the model, see Dardanoni *et al.*, 2016). To examine how perceived inequality and individual characteristics affect the $Y^d_1, \ldots, Y^d_K$, we follow a three-step strategy.

In the first step, we fit a set of simple univariate ordered logit models $\mathbf{B}_1$ such that $Y^d_1, \ldots, Y^d_K$ are assumed as independent. We then compare the independent model $\mathbf{B}_1$ with the multivariate model $\mathbf{B}_2$ including the bivariate associations (namely, the global log-odds ratios in Appendix A) in order to explore the existence of potential residual association due to unobserved factors. Model $\mathbf{B}_2$ implies that only the marginal logits depend on covariates, that the bivariate interaction terms are different across levels of response, and that higher-order interactions are set to zero.[2] To determine the complexity that is necessary to describe the association between $Y^d_1, \ldots, Y^d_K$, an approach is to fit, after model $\mathbf{B}_2$, the same model including three-factor interaction terms ($\mathbf{B}_3$), and so on, up to $\mathbf{B}_K$. From this perspective, $\mathbf{B}_{K-1}$ is a special case of $\mathbf{B}_K$; then, the null hypothesis that

[2]Note that the independent model $\mathbf{B}_1$ is simply model $\mathbf{B}_2$, where the bivariate interaction terms are set to zero.

$\mathbf{B}_{K-1}$ is nested in $\mathbf{B}_K$ can be tested by a simple LR test (Agresti, 2013). Following this approach we determine which model and order of interactions are better suited to describe the data.

In the second step we exploit a convenient feature of the multivariate ordered regression model: hypotheses of interest can be expressed in the form of linear equality constraints on the vector of model parameters. An important set of restrictions that we are going to test after the first step is the assumption that the association parameters do not depend on the cut points: an assumption which is the multivariate analog of the Plackett distribution (Plackett, 1965). In this case, the association is determined by a single parameter, as in the normal distribution; that is, we have a formal test of the Plackett assumption as $\lambda_{k,m;j,h} = \lambda_{k;j}$ where $j \neq k$ and m, h are the categories of the responses (m=h=1,2). We call this model $\mathbf{P}_2$ when we test the bivariate association, $\mathbf{P}_3$ when the association is among three indicators, and so on, up to $\mathbf{P}_K$. Again, we test with the LR statistics which, among these models, best describes the data. We also test if the Plackett restrictions fit the data better than the base model by running LR statistics between the **B** models and the **P** models.

Once the structure of association among indicators has been determined, in the third step we investigate the role played by covariates by estimating an extended model **E** which takes into account two potential effects of $\boldsymbol{x}$ on the joint distribution of $Y_1, \ldots, Y_K$. The first effect derives from relaxing the parallel lines assumption (see, e.g., Williams, 2006), which assumes that the γs do not differ across categories of Y_k. The second is on the interaction terms; we allow the latter to depend on $\boldsymbol{x}$. In particular, we estimate **E**, an *extended model* to evaluate whether the covariates, in addition to affecting the marginal distribution of the responses, also have a direct effect on their association.

As the three-step strategy relies on the estimation of a multivariate system of equations, it provides a richer description of how individual characteristics affect the joint distribution $Y_1^d, \ldots, Y_K^d$, and how these indicators are related to each other.

4. Data

The data used in this paper come from the Social Inequality module of the ISSP, the International Social Survey Programme. The last wave was collected in 2009 and it has been applied to the analysis of preferences and subjective values on inequality and redistribution (see, e.g., Corneo and Grüner, 2000; Suhrcke, 2001; Kuhn, 2011; Niehues, 2014; Gimpelson and Treisman, 2015; Brunori, 2017). We restrict our analysis to 19 OECD countries for a total of 16,1226 observations: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Italy, Japan, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, the United Kingdom (U.K.), and the United States (U.S.).[3]

[3]While the OECD includes 35 countries, many of them are not surveyed by the ISSP's pertinent module and others have been dropped from our empirical analysis because of missing observations on some relevant variables.

TABLE 1
Indicators by Domain

Domain of perception	Indicator	Description
Inequality of outcome	*logdif*	Perceived level of income differences among higher and lower professions
Inequality of outcome	*gtframe*	Perceived level of income differences among seven social classes (frames)
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	*polconn*	How important is having political connections?
Inequality of opportunity	*pgender*	How important is a person's gender?
Inequality of opportunity	*pedu*	How important is having well-educated parents?
Inequality of opportunity	*pwork*	How important is hard work?
Unfairness	*unfaired*	Just/unjust that rich people can buy better education than poor people?
Unfairness	*unfairheal*	Just/unjust that rich people can buy better healthcare than poor people?
Unfairness	*difinc*	Differences in income in your country are too large
Unfairness	*unlegit*	Unfairness of income inequality according to *logdif*
Unfairness	*fairframe*	Unfairness of income inequality according to *gtframe*

4.1. *Dependent Variables*

Many available indicators are potential measures of perceived inequality. Table 1 identifies the indicators used in this paper to capture each domain of perceived inequality.

Because the model's estimation requires indicators to take the same number of response categories, we rearrange the variables from 0 to 2, with increasing numbers associated with higher perceptions of inequality.[4] We describe how each variable is constructed for the three domains considered, starting with "Inequality of Outcome." *logdif* captures individual opinions about the distribution of incomes in society. It is constructed using the strategy suggested in Jasso (2007) that exploits survey questions about individual opinions on the earnings of certain professions. In particular, the ISSP question is "About how much do you think a [profession] earns?" and the professions are: doctor in general practice, a chairman of a large national corporation, a shop assistant, an unskilled worker, and a cabinet minister. Although this is a subset of all occupations, their range is wide, spanning from elite (chairman and doctor) to low (unskilled worker and shop assistant) professions. To create an index of the subjective degree of pay inequality for each respondent, we identify the highest- and lowest-paid profession and then we compute the logarithm of its ratio. Then we split the individual estimated distribution into three tertiles to create an ordered variable from the lowest to the highest level of that distribution.

gtframe derives from a question that asks individuals to frame the societal distribution of income according to five diagrams. They range from pyramidal societies (more unequal) to diamond-shaped societies (more equal). We construct

[4]In the pertinent ISSP Survey, most indicators in Table 1 range between three and five categories except *logdif*, *gtframe*, *unlegit* and *fairframe*, construction whose is described in this section.

a variable that takes 0 when the respondent reports more equal society, 1 when she perceives a society with only a few people being at the bottom, and 2 when she perceives a more unequal society with a small elite at the top, very few people in the middle, and most of the people at the bottom.

The last three indicators of the domain "Inequality of Outcome," *conflict*, *conflictr*, and *conflictm*, correspond to three questions that ask the respondent's opinion about the existence, in her country, of conflicts among the following social groups: 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 individual perceives in society.[5]

The indicators relative to domain "Inequality of Opportunity" correspond to a set of questions that ask individuals how important certain factors are to get ahead in life: coming from a wealthy family (*wfam*), political connections (*polconn*), gender (*pgender*), parents' education (*pedu*), and hard work (*pwork*). All questions have a five-point scale, from "not important at all" to "essential." For the first four indicators, we construct variables that take 0 if the respondent answers "Not important at all" or "not very important," 1 if he answers "Fairly important," or 2 if he answers "very important" or "essential." For the last one, *pwork*, the order is inverted since, as explained in Brunori (2017), it corresponds to a question about the role of effort and choice in determining success.[6]

In the "Unfairness" domain, the indicators *unfaired* and *unfairheal* correspond, respectively, to the following questions: "Is it just or unjust—right or wrong—that people with higher incomes can buy better education than people with lower incomes?"; "Is it just or unjust—right or wrong—that people with higher incomes can buy better healthcare than people with lower incomes?" As above, for these five-point scale questions, we construct indicators that take 0 if the respondent answers "Very just, definitely right" or "Somewhat just, right," 1 if she answers "Neither just nor unjust, mixed feelings," or 2 if she answers "Somewhat unjust, wrong" or "Very unjust, definitely wrong."

The indicator *difinc* derives from the following assertion: "Differences in income are too large." The answers range on a five-point scale, from "Strongly agree" to "Strongly disagree." We apply the same criterion to characterize the indicator along three levels of response: 0 ("Strongly disagree" or "disagree"), 1 ("Neither agree" or "disagree"), or 2 ("Agree" or "Strongly agree").

Finally, the indicators *unlegit* and *fairframe* are both constructed following the strategy proposed by Jasso (2007). She elaborates a ratio logarithm index to evaluate individual perceptions about the legitimacy of inequality. The index compares the individuals' estimate of the distribution of a specific outcome (i.e. income) with their ideal distribution by constructing a distance between the two. As the distance increases, so does the individual perception of unfairness. To

[5]The original indicator has four categories. To create a three- category variable, we have collapsed the two highest categories into one.

[6]Although the relevant ISSP module includes further questions on the perceived distribution of opportunities, to reduce complexity only five of them have been selected for their relevance in the literature. The results do not change substantially if the indicators' categories are combined differently.

begin with, consider *unlegit*. Its ratio has *logdif* as numerator, while the denominator captures the normative judgments about how income should be distributed among the same five professions considered by *logdif*. In particular, the denominator comes from responses to the following question: "About how much do you think a [profession] *should* earn?" The ratio yields the distance between the individual estimates of perceived pay inequality and the ideal distribution. In order to construct an ordered variable, *unlegit* is 0 if the ratio takes value 0 (that is, when there is no distance between the perceived and ideal level of distribution), 1, or 2 as the ratio increases.

In the case of *fairframe*, the numerator is *gtframe*, while the denominator is constructed as *gtframe* but with a question on the ideal distribution of income: "These five diagrams show different types of society. What do you think it *ought* to be like—which would you prefer for your country?" When the ratio takes value 0, this means that individuals think that their society is perfect as it is; when the difference is equal to 1 or 2, individuals think that their society is increasingly more unequal than it should be. When the ratio takes a negative value, this means that individuals think that their society is more equal than it should be. Since we are interested in the distance between perceptions and the ideal society rather than the sign of such a distance, we replace negative values with the corresponding positive ones.

4.2. *Independent Variables*

The independent variables are grouped into categories: demographics, socioeconomic, self-positioning on a social scale, experiences of mobility, political orientation, and degree of religiosity. The first category includes gender and age (also the quadratic term). The second category comprises two dummies that proxy the level of education, if the individual is married if he is employed, and two dummies on the reported level of income. The third category includes two dummies indicating if the individual perceives herself to be at the top or in the center of the society on a ten-box scale in terms of social groups. The fourth category includes two dummies that indicate if the individual has experienced intergenerational upward or downward social mobility. Political orientation indicates if individuals position themselves on the Left on a question of party affiliation. The last category indicates if the individual considers himself as a religious person.[7] The descriptive statistics for the covariates are reported in Appendix B (in the Online Supporting Information), including the share of observation per country with respect to the entire sample from the ISSP dataset (ISSP, 2012).

5. Results

The study of the impact that the individual characteristics have on the observable indicators $Y_1^d, \ldots, Y_K^d$ sheds light on three areas of perceived

[7]The variable *religiosity* takes value 0 when the individual never attends religious services, 1 if he attends a few times per year, or 2 if he attends at least once a month.

TABLE 2
Comparison and Evaluation of Models

Model	Log-likelihood	LR test	dof	p-value
Inequality of outcome				
$\mathbf{B}_1$	−57,259.33	–	–	–
$\mathbf{B}_2$	−52,312.95	9,892.75	40	0.0000
$\mathbf{B}_3$	−52,268.49	88.91	80	0.2320
$\mathbf{P}_2$	−52,590.71	555.52	30	0.0000
$\mathbf{E}_2$	−51,367.36	1,891.19	392	0.0000
Inequality of opportunity				
$\mathbf{B}_1$	−63,948.54	–	–	–
$\mathbf{B}_2$	−63,948.54	6,610.43	40	0.0000
$\mathbf{B}_3$	−63,900.48	96.13	80	0.1056
$\mathbf{P}_2$	−64,139.39	381.69	30	0.0000
$\mathbf{E}_2$	−63,188.88	1,519.32	392	0.0000
Perceived unfairness				
$\mathbf{B}_1$	−59,075.74	–	–	–
$\mathbf{B}_2$	−54,504.81	9,141.86	40	0.0000
$\mathbf{B}_3$	−54,463.38	82.85	80	0.3917
$\mathbf{P}_2$	−54,868.18	726.76	30	0.0000
$\mathbf{E}_2$	−53,725.14	1,559.33	400	0.0000

Note: The LR test is constructed for the following hypotheses: model $\mathbf{B}_1$ nested in $\mathbf{B}_2$; $\mathbf{B}_2$ nested in $\mathbf{B}_3$; $\mathbf{P}_2$ nested in $\mathbf{B}_2$; $\mathbf{B}_2$ nested in $\mathbf{E}_2$.

inequality. The first area is concerned with the associations among indicators of perceived inequality; in particular, whether these associations exist and their taxonomy. We find evidence of a multidimensional unobserved heterogeneity that casts new light on the understanding of the determinants of perceived inequality.

The second area is concerned with the pattern that perceived inequality displays on a cross-country basis. International data provide a comparative assessment of the respondent's views that may be useful for policy purposes, especially if contrasted with objective indicators of inequality. The third area is the most insightful. It is concerned with the role of covariates on perceived inequality and, in particular, on the associations among indicators. Our model casts light on the respondent's perceptions at the micro level, deeper than any previous analysis. Our knowledge of the determinants of perceived inequality engages important, still unresolved, questions. In this section, we discuss the results for each area, starting with the association between indicators.

5.1. *Associations among Indicators*

Before modeling the joint distribution of the observable indicators $Y_1^d, \ldots, Y_K^d$, according to the three domains of perceived inequality introduced in Section 2, we estimate the independent model $\mathbf{B}_1$ where no association exists among indicators. Then, to explore the existence of potential residual association due to unobserved factors, we estimate the multivariate model $\mathbf{B}_2$ with bivariate associations. Both models assume that indicators depend on the covariates reported in Appendix B and on country dummies. We then test the null hypothesis of no residual association. Table 2 reports the values of the LR test, which is asymptotically distributed as a χ^2 with 40 *dof*. For each domain the null

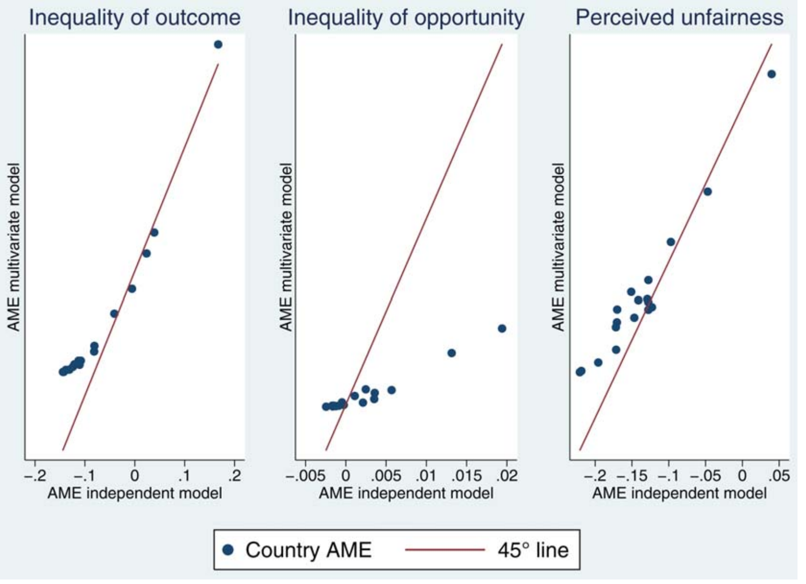

Figure 1. AME per Country for the Independent and Multivariate Model [Colour figure can be viewed at wileyonlinelibrary.com]

hypothesis is rejected, indicating that, conditional on observable covariates, the indicators are not independent.

In order to evaluate the effect of the covariates on the joint distribution of the indicators, it thus is crucial to take this residual source of association into account. For instance, Figure 1 depicts the estimated average marginal effects (AME) per country using models $\mathbf{B}_1$ and $\mathbf{B}_2$, respectively. A quick glance reveals that the AMEs are substantially different, since if the two models were the same, the estimated-country AME would lie on the diagonal. In particular, under the hypothesis of independence ($\mathbf{B}_1$), these effects are substantially higher in the first and third domains, while they are much lower in the second domain.

The difference between models $\mathbf{B}_1$ and $\mathbf{B}_2$ indicates how important is to take the residual correlation into account in evaluating how observable characteristics affect the joint distribution of the indicators. Moreover, the existence of these correlations supports the idea that the indicators are jointly measuring a common unobservable phenomenon.

While model $\mathbf{B}_2$ assumes the existence of bivariate associations among indicators, our empirical strategy also allows us to estimate model $\mathbf{B}_3$ with trivariate associations. As Table 2 shows, the null hypothesis that model $\mathbf{B}_2$ is nested in model $\mathbf{B}_3$ cannot be rejected for each domain of perceived inequality. The estimation process allows us to conclude that, for each domain, pairwise correlations describe the residual associations. We display the global log-odds of model $\mathbf{B}_2$ in Table 3 showing that the pairwise associations between indicators change substantially across the answer's response categories. To test whether these differences are systematic or due to random variations, we move to the second estimation

TABLE 3

Estimated Global Log-Odds Ratio $\boldsymbol{\lambda}^a$ Parameters for Model B_2

	conflictm conflictr	*conflictm conflict*	*conflictm logdif*	*conflictm gtframe*	*conflictr conflict*	*conflictr logdif*	*conflictr gtframe*	*conflict logdif*	*conflict gtframe*	*logdif gtframe*
Model B_2										
$\lambda_{1,1}$	3.1952***	3.2557***	−0.0831	0.0457	3.7107***	−0.1169	0.1995***	−0.2491***	0. 2034***	0.1812***
s.e.	0.09	0.09	0.08	0.08	0.09	0.07	0.07	0.08	0.07	0.05
$\lambda_{1,2}$	1.9398***	2.1942***	0.0909	0.0565	2.4068***	0.0686	0.2046***	0.042	0.2108***	0.0996**
s.e.	0.16	0.13	0.1	0.09	0.11	0.08	0.07	0.09	0.08	0.05
$\lambda_{2,1}$	1.4958***	1.4856***	0.0472	0.2817***	2.1432***	−0.0239	0.3832***	0.0627	0.3676***	0.1626***
s.e.	0.1	0.1	0.05	0.04	0.14	0.05	0.05	0.04	0.04	0.05
$\lambda_{2,2}$	1.7097***	1.9790***	0.1665***	0.3820***	2.9207***	0.0611	0.5039***	0.1238***	0. 5413***	0.1031**
s.e.	0.04	0.05	0.05	0.04	0.06	0.04	0.04	0.04	0.04	0.04
Model P_2										
λ	2.0162***	2.2237***	0.0962***	0.3028***	3.1271***	0.0138	0.4038***	0.0622*	0.4277***	0.1362***
s.e.	0.04	0.04	0.04	0.04	0.05	0.04	0.03	0.04	0.03	0.03
	wfam polconn	*wfam pgender*	*wfam pwork3*	*wfam pedu3*	*polconn pgender*	*polconn pwork3*	*polconn pedu3*	*pgender pwork3*	*pgender pedu3*	*pwork3 pedu3*
Model B_2										
$\lambda_{1,1}$	1.3440***	0.9709***	−0.0461	1.9164***	0.9207***	−0.1231***	0.9211***	−0.0359	0. 7534***	0.0230
s.e.	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.05	0.05
$\lambda_{1,2}$	1.4519***	0.9518***	−0.0445	1.4619***	1.0376***	−0.1624***	0.7943***	−0.0176	0. 5844***	−0.2398***
s.e.	0.06	0.07	0.04	0.04	0.06	0.04	0.04	0.04	0.04	0.04
$\lambda_{2,1}$	1.3328***	0.8785***	−0.0971**	1.6395***	0.9803***	−0.1147**	0.8915***	−0.2325***	0.7248***	−0.1067**
s.e.	0.05	0.05	0.05	0.08	0.05	0.05	0.07	0.06	0.08	0.05
$\lambda_{2,2}$	1.6754***	1.2205***	0.0628	1.9566***	1.2996***	−0.0069	1.0559***	−0.1093	0.9937***	−0.2534***
s.e.	0.05	0.06	0.05	0.05	0.07	0.06	0.05	0.07	0.06	0.04

Table 3 *Continued*

	wfam polconn	*wfam pgender*	*wfam pwork3*	*wfam pedu3*	*polconn pgender*	*polconn pwork3*	*polconn pedu3*	*pgender pwork3*	*pgender pedu3*	*pwork3 pedu3*
Model P_2										
λ	1.4386***	0.9907***	−0.0422	1.7842***	0.9977***	−0.1237***	0.9216***	−0.0500	0.7130***	−0.1607***
s.e.	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03
	unfaired unfairheal	*unfaired difinc*	*unfaired fairframe*	*unfaired unlegit*	*unfairheal difinc*	*unfairheal fairframe*	*unfairheal unlegit*	*difinc fairframe*	*difinc unlegit*	*fairframe unlegit*
Model B_2										
$\lambda_{1,1}$	3.3127***	0.8613***	0.3198***	0.4912***	0.9508***	0.3296***	0.6761***	0.7215***	1.3208***	0.4821***
s.e.	0.06	0.07	0.05	0.09	0.06	0.05	0.09	0.06	0.1	0.08
$\lambda_{1,2}$	2.4766***	0.5778***	0.2884***	0.2657***	0.6411***	0.3090***	0.3055***	0.8978***	0.7670***	0.2205***
s.e.	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.09	0.07	0.04
$\lambda_{2,1}$	2.3533***	0.8759***	0.3336***	0.6100***	0.9207***	0.3980***	0.6739***	0.7402***	1.2531***	0.4064***
s.e.	0.06	0.06	0.04	0.08	0.06	0.04	0.08	0.05	0.09	0.1
$\lambda_{2,2}$	3.1110***	0.8789***	0.3751***	0.3509***	0.8973***	0.4867***	0.3885***	0.8291***	0.7954***	0.3202***
s.e.	0.05	0.05	0.04	0.04	0.05	0.04	0.04	0.06	0.05	0.04
Model P_2										
λ	3.1939***	0.8357***	0.3598***	0.3744***	0.8709***	0.4140***	0.4243***	0.7778***	0. 9094***	0.2996***
s.e.	0.04	0.04	0.03	0.04	0.04	0.03	0.04	0.04	0.05	0.03

Note: For all equations, the control variables are gender, age, second-order polynomial of age, education, married, employed, income, self-positioning, social mobility, party affiliation, religiosity, and country dummies.

*,**,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

step and fit model $\mathbf{P}_2$: the associations among the indicators are now restricted not to vary across the response categories, as described in Section 3.1. Now, the null hypothesis that $\mathbf{P}_2$ is nested in $\mathbf{B}_2$ is rejected in all domains, as reported in Table 2.

If compared, the results from the models with ($\mathbf{P}_2$) and without ($\mathbf{B}_2$) restrictions on the residual association parameters reported in Table 3 provide further information for the analysis of the association among the indicators. Two results must be noted. First, restricted associations (that are similar to pairwise correlations employed in the literature) can be misleading. Consider, for instance, the first domain, inequality of outcome; in particular, the restricted association between *conflict* and *logdif*. The results of model $\mathbf{P}_2$ in Table 3 reveal that they are positively associated but ignore the real structure of the association, which can only be inferred when the base model $\mathbf{B}_2$ is estimated. Moreover, the association between the two indicators comes only from the pattern of responses (1,1) and (2,2) and, in the first case, the association is negative. Similarly, in the case of the inequality of opportunity domain and the indicators *pgender* and *pwork*, no restricted association can be detected, but they are negatively correlated if we consider the pattern of responses (2,1).

The second result on the association among the indicators confirms the existence and relevance of multidimensionality. Rejecting the Plackett restrictions, it can be noted that the size of the associations changes non-monotonically across the response categories. In particular, bivariate associations in model $\mathbf{B}_2$ reveal the existence of a multidimensional underlying unobserved heterogeneity. In search of further evidence, we plot the size of the global log-odds ratios among two of the most associated indicators in the first (*conflictm* and *conflict*), second (*wfam*, and *pedu*) and third (*unfaired* and *unfairheal*) domains, with their respective confidence intervals.[8] In Figure 2, we observe that the associations vary non-monotonically across the response categories. Not all indicators display the same behavior: some associations have a more linear trend, but a majority resembles the pattern in Figure 2, revealing the existence of a multidimensional underlying unobserved heterogeneity that systematically affects how respondents perceive inequality.[9]

To conclude, the possibility of destructuring associations among indicators across categories reveals specific features of perceived inequality. Note that $\lambda_{2,2}$ is, with few exceptions, always positive and strongly significant. Therefore, respondents who report a high level of perceived inequality in one indicator are likely to report a high level on other indicators. For instance, consider the indicators *wfam* and *pedu*: the odds that a respondent reports a high value of perceived inequality in the two indicators are 7.07 times greater than the odds of reporting a low value. As a general rule, we conclude that respondents who perceive a high level of inequality report the same high level in most indicators. In the following sections, we explore how covariates affect perceived inequality.

[8]Note that $\lambda_{1,2}$ and $\lambda_{2,1}$ are graphically represented in a lexicographic order, with the second indicator running faster.

[9]The other figures are available upon request.

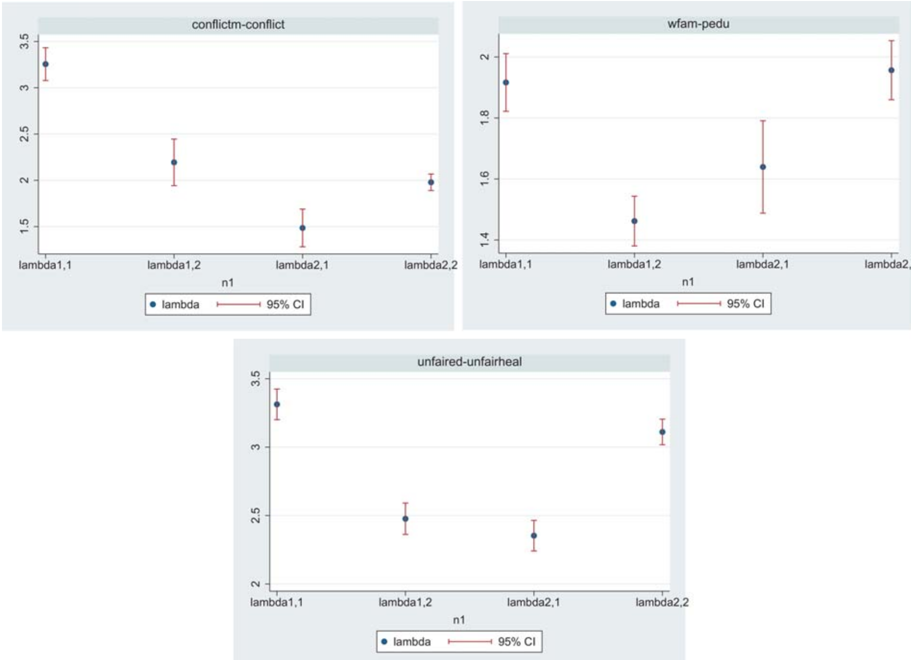

Figure 2. Global Log-Odds among Two Indicators in the Same Domain, with Confidence Intervals [Colour figure can be viewed at wileyonlinelibrary.com]

5.2. *Cross-Country Differences in Perceived Inequality*

The second area explored by our empirical analysis concerns cross-country differences for each domain of perceived inequality. In order to accomplish such a goal, we need to move to the third step of the estimation process. We thus estimate the *extended model* **E** to allow the interaction terms (in our case, the bivariate associations of the base model $\mathbf{B}_2$) to depend on **x** and the γs to vary across categories.[10] As reported in Table 2, the null that model $\mathbf{B}_2$ is nested in $\mathbf{E}_2$ is overwhelmingly rejected.

To explore cross-country differences for each domain of perceived inequality, we compute the predicted probabilities among domains from model $\mathbf{E}_2$. From the predicted joint distribution it is possible to recover the marginal probabilities of reporting the highest level of perceived inequality in at least three (out of five) indicators. Figure 3 reports these probabilities by country and ranks them from the lowest to the highest.

Some observations are appropriate. First, the ranges of the domains are quite different. Perceived inequality of outcome ranges from 0.07 (Denmark) to 0.90 (South Korea); perceived inequality of opportunity from 0.03 (New Zealand) to 0.26 (Austria); and perceived unfairness from 0.35 (New Zealand) to 0.80

[10]We relax the so-called parallel line assumption. Note that not all covariates violate such an assumption, as we report in the tables of Appendix B of the online Supporting Information. Here, we also report the results of the LR tests of the parallel line assumption for each covariate and domain.

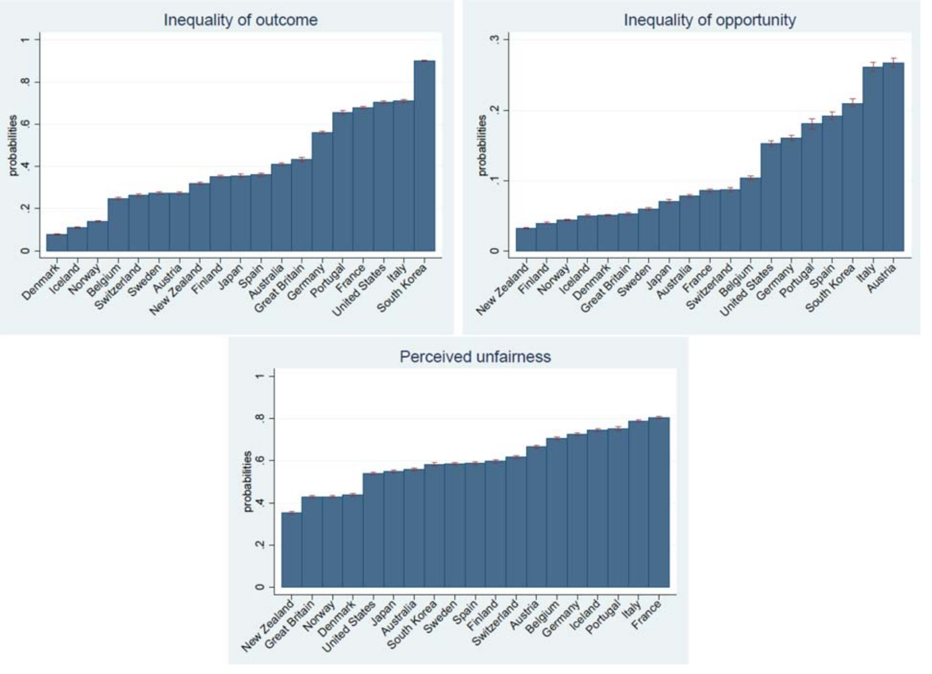

Figure 3. Countries with the Highest Levels of Perception in Inequality and Unfairness, with 95% Confidence Intervals [Colour figure can be viewed at wileyonlinelibrary.com]

(France). These differences in range come with different dispersions in terms of predicted probabilities. The latter is substantial for perceived inequality of outcome and not impressive for perceived inequality of opportunity. It follows that there is cross-country diversity in the estimation of the perceived inequality of outcome even if opportunities are perceived as not so unevenly distributed. The difference in the perception of inequality of outcome and opportunity could also explain why, in the third domain, the distances among countries are smaller than in the first domain. Respondents seem convinced that, as opportunities are open to many, inequality is not perceived as unfair because it is the outcome of circumstances under the individual's control.

A second feature that emerges from Figure 3 is country variability. Such variability can be clustered into macro regions, leading to the conclusion that perceived inequality—in particular, perceived unfairness—is dependent on cultural attitudes toward inequality. This confirms many empirical findings in the literature (Corneo and Grüner, 2000; Alesina *et al.*, 2001; Alesina and La Ferrara, 2005; Benabou and Tirole, 2006; Luttmer and Singhal, 2011) and, in particular, that Anglo-Saxon countries display lower levels of perceived unfairness than continental and Mediterranean countries.

A further feature revealed by Figure 3 concerns some unexpected country rankings in the three domains. For example, outside Europe, perceived inequality of outcome is quite strong in South Korea and the U.S., whereas in Europe this is the case in France and Italy. Note also that the position that these four countries

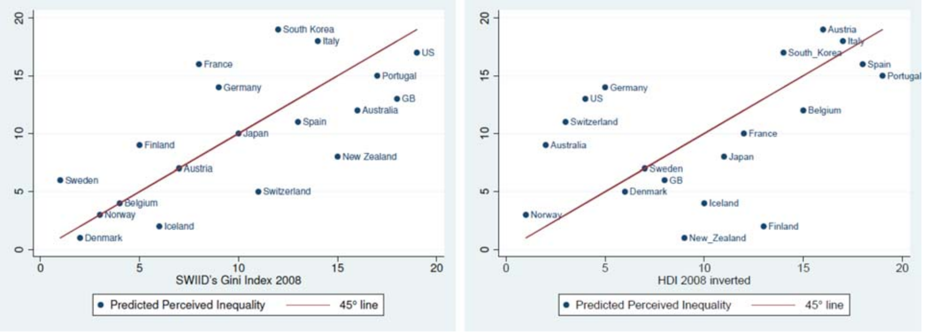

Figure 4. Perceived and Objective Inequality (Rank) [Colour figure can be viewed at wileyonlinelibrary.com]

occupy in the perceived inequality of outcome ranking is quite different from the perceived unfairness roster.

To complete the review of cross-country differences, we compare perceived with objective inequality. In particular, we rank countries with respect to the predicted probabilities of Figure 3 and some objective index of inequality of outcome and opportunity. We consider the Gini index as a measure of inequality of outcome (data from Solt, 2016, for the year 2008) and the inverse of the United Nation's Human Development Index as an objective measure of inequality of opportunity.[11] Plotting the subjective against the objective ranking for the inequality of outcome and opportunity domains, we display the distance between perceptions and the objective level of inequality in Figure 4.

The first observation is that respondents in the U.S., the U.K., Australia, and New Zealand underestimate the objective level of inequality of outcome, whereas in Germany, Italy, France, Sweden and Finland respondents overestimate it. This result is in line with Niehues (2014), who predicts that Americans systematically underestimate inequality, while Germans overestimate it. As noted, the difference between the level of objective inequality and its perception has political relevance. In the Italian case, the overestimation of inequality is likely to lead to preferences for political parties that favor the overhaul of the incumbent political establishment.

The second observation concerns inequality of opportunity for which three clusters of countries can be identified. Southern European countries such as Spain, Italy, and Portugal have the highest level of objective inequality of opportunity and perceptions are close to reality—the Spanish and the Portuguese slightly underestimate it, while Italians overestimate it. Respondents in another group of countries, markedly Germany, the U.S., Australia, and Switzerland, tend to overestimate the distribution of opportunities, whereas respondents in all the remaining countries—the majority in our sample—underestimate it.

[11]Brunori *et al.* (2013) offer an overview on the studies that measure inequality of opportunity indexes. Most of them focus on specific countries such as the U.S. or on restricted samples such as Europe. Since the overview shows that these indexes are correlated with the Human Development Index, we prefer to use the latter because of its wider country coverage.

5.3. *The Effect of Covariates on Individual Perceptions of Inequality*

We now turn our attention on how individual characteristics affect both manifest indicators and their associations capturing the underlying unobserved perceived inequality. To this end, we propose two strategies. First, we compute the AME of the covariates on the joint distribution of the indicators and compare them to the marginal effects of model $\mathbf{B}_1$ that assumes independence among indicators. Second, we report marginal and conditional survival functions when a single covariate changes.[12]

Covariates

Table 4 reports the AME for each domain when the residual correlation is (not) taken into account by model $\mathbf{E}_2$ ($\mathbf{B}_1$). The table shows both the joint probability of reporting a value greater or equal to 1 and a value equal to 2 for the independent (first and second columns) and the multivariate (third and fourth columns) models. To start with, consider the domain "Inequality of outcome." Respondents with intermediate and high incomes, with a middle or top-class social position and strong religiosity jointly report lower levels of perceived inequality. The results on income and self-positioning confirm the findings of Cruces *et al*. (2013). On the contrary, adult respondents and those leaning to the Left in politics tend to jointly report more inequality. The first effect diverges from the literature, which finds that younger people are more adverse to inequality, while the second is in line with the literature (Alesina and Giuliano, 2009).

The difference between models $\mathbf{B}_1$ and $\mathbf{E}_2$ can be relevant. For instance, consider how *toppos* affects the probability of reporting a value greater than 1 in the domain of inequality of outcome. The difference between coefficients in models $\mathbf{B}_1$ and $\mathbf{E}_2$ is about 20 percent, with the former predicting a stronger effect. Thus unobserved heterogeneity plays a key role in modeling perceived inequality.

Unobserved heterogeneity plays no less a role in the second domain, inequality of opportunity. Respondents who have intermediate and high incomes, who enjoy a middle or top-class social position, and are religious perceive less inequality of opportunity, unlike Left-leaning individuals. Respondents with intermediate or high levels of education perceive less inequality of opportunity, although education has no effect on perceived inequality of outcome. This confirms the finding of Alesina and Giuliano (2009). Note that, contrary to Brunori (2017), we do not observe any effect of experience of social mobility on perceived inequality of opportunity. If combined with behavioral assumptions about political sentiments (and resentments), one may interpret the relationship between the emergence of populism and the irrelevance of experiences of social mobility. Within the boundary of this paper, a crucial point is confirmed: if unobserved heterogeneity is taken into account, some factors may produce no effect on perceptions. An index that aggregates the manifest indicators of perceived inequality to test for theories related to social mobility (e.g. Hirschman and Rothschild, 1973; Benabou and Ok, 2001) may then be problematic.

[12]The full set of estimated parameters is reported in Appendix B.

TABLE 4
Average Marginal Effects

	Inequality of outcome				Inequality of opportunity				Perceived unfairness			
	Model $\mathbf{B_1}$		Model $\mathbf{E_2}$		Model $\mathbf{B_1}$		Model $\mathbf{E_2}$		Model $\mathbf{B_1}$		Model $\mathbf{E_2}$	
Variable	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$
fem	−0.0043	0.0105**	−0.0100**	0.0007	−0.0008	−0.0001***	0.0110***	0.0010*	0.0415***	0.0573***	0.0359***	0.0504***
s.e.	0.0048	0.0051	0.0047	0.0068	0.0010	0.0000	0.0032	0.0006	0.0042	0.0054	0.0038	0.0065
age	0.0590***	0.0195*	0.0632***	0.0398**	0.0104***	0.0004***	0.0330***	0.0079***	0.0595***	0.0986***	0.0539***	0.0988***
s.e.	0.0100	0.0110	0.0096	0.0156	0.0023	0.0001	0.0065	0.0017	0.0093	0.0113	0.0080	0.0132
age2	−0.4268***	−0.0872	−0.4607***	−0.2340	−0.0824***	−0.0035***	−0.2798***	−0.0669***	−0.5315***	−0.8176***	−0.4851***	−0.8217***
s.e.	0.1011	0.1107	0.0979	0.1618	0.0230	0.0009	0.0648	0.0161	0.0954	0.1153	0.0811	0.1333
medqual	−0.0006	−0.0079	0.0015	0.0013	−0.0013	−0.0001***	−0.0126***	−0.0043***	0.0047	−0.0055	−0.0010	−0.0008
s.e.	0.0062	0.0076	0.0060	0.0098	0.0016	0.0001	0.0049	0.0010	0.0076	0.0083	0.0066	0.0093
highqual	−0.0162**	−0.0367***	−0.0084	−0.0166	0.0086***	−0.0001**	0.0038	−0.0041***	−0.0286***	−0.0498***	−0.0266***	−0.0417***
s.e.	0.0069	0.0074	0.0065	0.0103	0.0021	0.0001	0.0053	0.0010	0.0079	0.0079	0.0068	0.0096
married	−0.0054	−0.0122**	−0.0014	−0.0021	−0.0056***	−0.0002***	−0.0151***	−0.0026***	−0.0054	−0.0057	−0.0045	−0.0064
s.e.	0.0042	0.0049	0.0040	0.0069	0.0010	0.0000	0.0030	0.0006	0.0046	0.0054	0.0039	0.0063
employed	−0.0117**	−0.0162***	−0.0111**	−0.0130	−0.0030**	−0.0001**	−0.0030	−0.0004	0.0062	0.0103	0.0052	0.0082
s.e.	0.0047	0.0055	0.0047	0.0085	0.0013	0.0000	0.0039	0.0007	0.0056	0.0068	0.0048	0.0084
incq3d2	−0.0082	−0.0131**	−0.0071	−0.0175**	−0.0013	−0.0001	−0.0047	−0.0013*	−0.0098*	−0.0168**	−0.0069	−0.0119
s.e.	0.0051	0.0059	0.0050	0.0087	0.0013	0.0001	0.0040	0.0008	0.0058	0.0067	0.0048	0.0082
incq3d3	−0.0111**	−0.0357***	−0.0097*	−0.0336***	0.0002	−0.0002***	−0.0009	−0.0025***	−0.0596***	−0.0848***	−0.0403***	−0.0681***
s.e.	0.0053	0.0059	0.0054	0.0093	0.0015	0.0000	0.0046	0.0008	0.0068	0.0063	0.0057	0.0085
toppos	−0.1267***	−0.0988***	−0.1055***	−0.1007***	−0.0058***	−0.0002***	−0.0247***	−0.0041***	−0.1814***	−0.1653***	−0.1535***	−0.1872***
s.e.	0.0087	0.0076	0.0081	0.0098	0.0020	0.0001	0.0057	0.0011	0.0095	0.0075	0.0092	0.0101
centerpos	−0.0556***	−0.0673***	−0.0498***	−0.0684***	−0.0058***	−0.0003***	−0.0170***	−0.0036***	−0.0636***	−0.0910***	−0.0591***	−0.1011***
s.e.	0.0077	0.0076	0.0071	0.0105	0.0016	0.0001	0.0048	0.0010	0.0044	0.0044	0.0037	0.0048
mobup	0.0017	0.0017	−0.0006	−0.0016	0.0022**	0.0001**	0.0043	0.0006	0.0004	−0.0069	−0.0011	−0.0141**
s.e.	0.0047	0.0056	0.0044	0.0074	0.0011	0.0000	0.0035	0.0007	0.0048	0.0054	0.0040	0.0064
mobdown	0.0088	0.0113*	0.0056	0.0016	0.0068***	0.0002***	0.0077*	0.0013	0.0017	0.0026	0.0014	0.0068
s.e.	0.0054	0.0069	0.0052	0.0094	0.0017	0.0001	0.0043	0.0009	0.0058	0.0069	0.0049	0.0084
leftparty	0.0366***	0.0496***	0. 0321***	0.0479***	0.0127***	0.0005***	0.0283***	0.0052***	0.0700***	0.1451***	0.0546***	0.1075***
s.e.	0.0036	0.0048	0.0034	0.0062	0.0016	0.0001	0.0035	0.0008	0.0028	0.0035	0.0023	0.0036
religiosity	−0.0101***	−0.0104***	−0.0093***	−0.0112**	0.0001	−0.0001	−0.0037*	−0.0011**	−0.0117***	−0.0279***	−0.0107***	−0.0308***
s.e.	0.0026	0.0033	0.0026	0.0046	0.0007	0.0001	0.0021	0.0004	0.0031	0.0040	0.0028	0.0050

Notes: Bootstrapped standard errors are based on 1,000 repetitions. Country dummies are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The joint probability of reporting a high level of perceived unfairness reduces for religious respondents with intermediate and high incomes and a middle or top-class social position. Note that the size of the coefficients can be different between the independent and the multivariate model because of unobserved heterogeneity. For instance, the marginal effect of *incq3d3* is substantially different between the two models. Female, middle-aged, and Left-leaning respondents perceive more unfairness in the distribution, confirming the findings of Andreoni and Vesterlund (2001) and Alesina and Giuliano (2009). Moreover, educated people perceive less unfairness than uneducated people. Finally, we find support for the self-esteem bias theory (Miller and Ross, 1975): respondents who have a better job than their fathers perceive less unfairness because they attribute success to factors under their control.

The empirical analysis on the marginal effects of the covariates confirms the gains secured by our approach, which sheds light on and measures how different characteristics of the respondents lead to different levels of perceived inequality. Take the case of income. Poor respondents perceive higher levels of inequality, no matter what domain we consider—and so do individuals who perceive low levels of inequality. The systematic bias is a useful signal for policy purposes. To the extent that perceived inequality motivates protests and populist responses, the figures in Table 4 expose the risk associated with the legitimate sustainability of a political order.

The case of the recent American presidential election fits. Globalization has been hardest for white, low- education, middle-aged Americans (Case and Deaton, 2015; Milanovic, 2016). Information about their perception of inequality could help to identify which target policy should pursue, how to alleviate their suffering, and how best to tackle the issue of political legitimacy.

Marginal and Survival Functions

The ratios of marginal and conditional survival functions when a single covariate changes offer additional insights on the effect of covariates on perceived inequality. The survival function describes the probability that an observable indicator Y_k takes on a value greater than a specific category (0, 1, or 2, in our case). Such a probability can be extended to the multivariate case by jointly considering $Y_k \geq h$ and $Y_j \geq m$. To study how this probability changes with respect to a covariate, we use a counterfactual that compares two fictitious respondents with all covariates set to the mean, except for the covariate of interest, which is set to the maximum and minimum level. Since most of our covariates are binary variables, they are set between 0 and 1. In this case, the estimated ratio between the survival functions is given by:

$$\frac{Pr(Y_j \geq m, Y_k \geq h|\, x=1, \bar{z})}{Pr(Y_j \geq m, Y_k \geq h|\, x=0, \bar{z})}, \tag{4}$$

where $\bar{z}$ is the set of covariates at the mean, excluding the variable of interest x. We estimate the marginal survival functions for all indicators per domain and the conditional survival functions for four indicators, conditional to the one that is taken as the base category. Table 5 shows the survival function ratios for the

TABLE 5

The Marginal and Conditional Survival Functions in the Domain "Inequality of Opportunity"

	wfam		*polconn*		*pgender*		*pedu*		*pwork*	
	$y_k > 1$	s.e.	$y_k > 1$	s.e.	$y_k > 1$	s.e.	$y_k > 1$	s.e.	$y_k > 1$	s.e.
medqual										
Marginal	0.8799***	0.0410	1.0016	0.0452	0.7672***	0.0434	1.0555*	0.0289	0.9771	0.0286
$y_j > 1$			0.9708	0.0424	0.7602***	0.0559	1.0090	0.0158	0.9727	0.0451
highqual										
Marginal	0.9319	0.0462	0.9080*	0.0481	0.8129***	0.0490	1.2259***	0.0340	0.9385**	0.0271
$y_j > 1$			0.8853***	0.0422	0.8219***	0.0655	1.0581***	0.0165	0.9736	0.0444
employed										
Marginal	0.9329**	0.0321	0.9332*	0.0365	0.9435	0.0407	0.9521**	0.0239	1.0091	0.0208
$y_j > 1$			1.0207	0.0361	1.0036	0.0539	0.9709*	0.0153	1.0034	0.0346
incq3d2										
Marginal	0.9935	0.0328	0.9782	0.0348	0.9437	0.0374	1.0021	0.0255	0.9878	0.0224
$y_j > 1$			0.9574	0.0353	0.9841	0.0554	0.9971	0.0123	0.9707	0.0374
incq3d3										
Marginal	0.9349	0.0428	0.9097**	0.0386	0.8807**	0.0483	1.0263	0.0286	0.8692***	0.0261
$y_j > 1$			0.9841	0.0425	0.9427	0.0671	1.0035	0.0161	0.8495***	0.0428
toppos										
Marginal	0.7217***	0.0497	0.7668***	0.0498	0.8819**	0.0569	1.1450***	0.0434	0.9531	0.0332
$y_j > 1$			0.7539***	0.0529	0.8759	0.0841	1.0521**	0.0209	1.062	0.0581
centerpos										
Marginal	0.7189***	0.0333	0.7342***	0.0354	0.8784***	0.0442	0.9149***	0.0290	0.9938	0.0238
$y_j > 1$			0.8399***	0.0446	0.8935*	0.0579	0.9912	0.0164	1.0247	0.0405
mobdown										
Marginal	1.1423***	0.0387	1.0618	0.0395	1.1356***	0.0411	1.1278***	0.0285	0.9861	0.0182
$y_j > 1$			0.9284**	0.0353	0.9857	0.0494	1.0135	0.0135	0.9828	0.0359
mobup										
Marginal	1.0582*	0.0343	1.0842***	0.0326	1.0431	0.0314	1.0135	0.0193	0.9557***	0.0162
$y_j > 1$			1.0236	0.0309	0.9799	0.0449	0.9955	0.0108	0.9759	0.0291
leftparty										
Marginal	1.1791***	0.0275	1.1626***	0.0327	1.2610***	0.0341	1.0868***	0.0194	1.1477***	0.0165
$y_j > 1$			1.0556*	0.0315	1.1768***	0.0477	0.9976	0.0110	1.1076***	0.0262
religiosity										
Marginal	0.9485***	0.0164	1.0172	0.0190	1.0248	0.0232	1.012	0.0124	0.9777**	0.0103
$y_j > 1$			1.0034	0.0187	0.9997	0.0307	0.9969	0.0078	0.9483***	0.0196

Notes: y_j is the base indicator for the domain "Inequality of opportunity" that corresponds to *wfam*.
Bootstrapped standard errors are based on 1,000 repetitions.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

highest level of perceived inequality of opportunity, taking *wfam* as the base indicator.[13]

Two results must be noted. First, we observe that marginal probabilities differ, sometimes substantially, across indicators. Second, since we are modeling the effect of the covariates on the association among indicators through conditional marginal probabilities, we may shed light on how the perception of inequality is formed.

The effect of covariates on their associations reveals a multifaceted picture, with substantial variation among indicators. As an example, consider *leftparty*, which is a covariate that reveals the respondent's political views. Left-leaning respondents are 17 percent more likely than Right-leaning respondents to believe that parents' wealth is important for success, 16 percent that political connections count, 26 percent that gender is relevant, and 8 percent that parents' education is important, and they are also 14 percent more likely to believe that effort is not rewarded in society. Our findings confirm a common claim in the literature that certain partisan and political visions are related to specific perceptions of economic conditions (Evans and Andersen, 2006; Tilley and Hobolt, 2011)—or, to put it differently, that political views are closely linked to the weight that a person attributes to structural circumstances (family wealth, gender, etc.) for achievement (Kluegel and Smith, 1986; Alesina and Angeletos, 2005; Benabou and Tirole, 2006; Alesina and Fuchs-Schündeln, 2007; Alesina and Giuliano, 2009).

In Table 5, we can also assess the effect of *leftparty* on the association among indicators through the conditional survival functions. If conditioned to *wfam*, individuals are likely to believe that political connections (5 percent) and gender (17 percent) are important in getting ahead in life, while effort is not (10 percent). While these figures confirm the claims in the literature on the relation between individuals' political views and their understanding of opportunity, they also offer a fresh perspective on the effect of *leftparty* on other dimensions of perceived inequality of opportunity, strengthening the claims made in the literature.

Another variable that is often scrutinized in the literature is *mobdown*, which indicates whether the respondent has personal experience of downward social mobility. As observed in Table 4, *mobdown* has no effect on the joint probability of reporting a high level of perceived inequality. We can dig further on this result using the marginal and conditional survival functions. We find that individuals who experience a downward movement on the social ladder are 14 percent more likely to believe that parents' wealth is important, 13 percent that gender is important, and 12 percent that parents' education is important. However, the effect on the other indicators is not significative, revealing how crucial is multidimensionality in the study of the perception of inequality. Contrary to *leftparty*, personal experiences such as downward social mobility affect only certain dimensions of perceived inequality of opportunity. Such an inconsistency is even starker when we condition for our base indicator (*wfam*): respondents who have experienced downward social mobility and still believe that being born in a wealthy family counts are less likely to believe that political connections (7 percent) are important.

[13]The tables with marginal and conditional survival functions for the other domains are reported in Appendix B.

The example provided by *mobdown* is illustrative of the advantages that our approach can offer to the understanding of perceived inequality and to the theories that use unobservable variables (such as effort or control) to shed light on economic phenomena (such as a preference for redistribution or the role of self-esteem). These advantages could have not been listed without our, more refined approach about the determinants of perceived inequality.

Another case suspected of inconsistency and revealed by our methodology is given by the variable *toppos*, which captures whether respondents place themselves in the uppermost echelon of society. These individuals are less likely to believe that parents' wealth (28 percent), political connections (23 percent), and gender (12 percent) are important. However, they are also more likely to consider parents' education (14 percent) as important, while the effect on effort is negligible. We would expect from the theory that top self-positioning has a negative effect on perceived inequality (Cruces *et al.*, 2013). Table 5 challenges this claim. If we restrict our attention to respondents who believe that parents' wealth is important, top-positioning individuals are more than 25 percent less likely to believe that political connections are important and 5 percent more likely to consider parents' education as relevant. Once again, this result shows the importance of modeling perceived inequality with a multivariate approach that handles unobserved heterogeneity and multidimensionality.

Let us review the data for two further covariates: the level of income, *incq3d3*, and the level of education, *highequal*. As far as income is concerned, we would expect the most well-off to report a lower perception of inequality (Cruces *et al.*, 2013). The intuition is confirmed by the data, but only for some indicators, *polconn*, *pgender*, and *pwork*. The conditional survival estimates reveal that, among those who believe that parents' wealth is important, the rich also consider that effort is important, while the effect on other associations is negligible. Once again, the multidimensional nature of perceived inequality operates.

Finally, consider the level of education, *highed*. Theoretical predictions about the effects of education on views about inequality are ambiguous. On the one hand, education should be related to social mobility and income, so the most educated should report lower levels of perceived inequality. On the other hand, education fosters inclusive values and the belief that something must be done for the worse-off. Structural circumstances may therefore prevail in the formation of opinions about inequality, leading to a higher perception (Szirmal, 1988; Alesina and Giuliano, 2009; Cruces *et al.*, 2013). Table 5 supports both explanations when multidimensionality is taken into account: the most educated are 10 percent less likely to report that political connections are important and 18 percent and 7 percent, respectively, that gender counts while effort does not. However, the most educated individuals are 22 percent more likely to believe that parents' education is important. The effects are almost the same when conditioning to *wfam*.

To conclude, the results shown in this section confirm the importance of addressing questions about the determinants of perceived inequality with a model that accounts for both the different dimensions that compose it and the structure of the association among indicators. Observable covariates can have different and even contrasting effects. Unobservables must be dealt with in a model that allows associations among indicators to vary across response categories.

6. Conclusion

In this paper, we have presented an empirical analysis of perceived inequality. We have proposed a novel approach that explicitly acknowledges its multidimensionality and essential contestedness. To accommodate these features, we have constructed an empirical approach that studies how the observable characteristics of the respondents affect the joint distribution of multiple indicators of perceived inequality through the estimation of a system of equations that uses a multivariate ordered logit model. In particular, we have explored how individual characteristics of the respondents affect the observable indicators and, ultimately, capture the underlying unobserved level of perceived inequality.

The approach that we propose yields several insights on perceived inequality. Prominent are the findings on the joint distribution of multiple indicators and the effect of covariates on the level of association among indicators. As we argued, the information that these findings provide qualifies the theoretical predictions about perceived inequality and sheds light on the relation between perceived inequality and the latent variables that contribute to determine its extent.

If applied to policies and politics, the approach engages the main findings of the literature on inequality. As we have noted, previous experiences of social mobility, political views, self-positioning in society, parents' wealth, and education, as well as other subjective variables, bear important consequences on the perception of inequality. If combined with appropriate behavioral assumptions, our approach digs deeply into the perception of inequality and sets the basis for further research on the effect of perceived inequality on the economy and society and, ultimately, on the construction of a fully fledged measure of perceived inequality.

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Supporting Information

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

Appendix A The Multivariate Ordered Logit
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Table B.4: Estimated Intercept and Covariates Coefficient on Log-Odds Ratios under the Model E in Domain "Inequality of Outcome"
Table B.5: Estimated Covariates Coefficients in Univariate Logits under Model E in Domain "Inequality of Opportunity"
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