AN EMPIRICAL ANALYSIS OF THE DETERMINANTS OF PERCEIVED INEQUALITY

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Abstract. 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.

Keywords: Inequality of outcome - Inequality of opportunity - Fairness - Perception of inequality

JEL Classification: 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 is 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 analytical 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., Jasso, 2007; Cruces *et al.*, 2013; Niehues, 2014; Gimpelson and Treisman, 2015; Brunori, 2016), 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 individuals 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 be 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 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 get 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 whose answers 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 analytical 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, 2016; 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 (Orkeny and Szekelyi, 2000; Kluegel and Miyano, 1995; Brunori, 2016). 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 analytical 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 whose differences 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., wellbeing or happiness) outcome. One way to assess perceived inequality of outcome is to ask views about the gap between different social groups. Kelley and Zagorsky (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 in 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 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 (2016) emphasizes the role of cultural and social variables as well as of personal experiences of inter-generational social mobility to determine the respondents' perception of inequality of opportunity.

The final interpretation of perceived inequality that we propose is *perceived unfairness* that 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 Roemer and Trannoy, 2016 and Amiel *et al.*, 2015). 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 (e.g., opportunity) 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 respondents value differently distinct aspects of the same domain of perceived inequality, it is plausible to expect that perceived inequality may heterogeneously affect how respondents frame their indicators' answer because there is no single pathway that the observable indicators admit to reconstruct the perception.

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, socio-economic and ideological. For example, demographic determinants suggest that women are more likely than men to perceive a distribution as unfair (Jasso and Wegener, 2000 and Alesina and Giuliano, 2009), that gender affects altruism (Andreoni and Versterlund, 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).

Socio-economic 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 Richards, 1981, Persson and Tabellini, 1994, Ravallion and Lokshin, 2000, Suhrcke, 2001 and Corneo and Grüner, 2000, 2002). Cruces *et al.*, 2013 find that the level of income of the reference group explains the gap between objective and perceived inequality. Income is indirectly related to perceived inequality also through expectations about future income because the latter bear on the justification of inequality (Hirschman, 1973; Benabou and Ok, 2001). In particular, the poor's belief that the income ladder may be climbed favors the acceptance of a certain degree of inequality to avoid redistributive consequences.

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 Angeletos 2005, Alesina and Gleaser 2004, Benabou and Tirole 2006, Bavetta and Navarra 2012). Beside, political orientation, cultural and religious attitudes also affect how inequality is perceived (Alesina and Giuliano, 2009; Suhrcke, 2001; Weber, 1930; Benabou and Tirole, 2006; Lübker, 2004).

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

[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.

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.

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 assume that the ith individual's perceived inequality in a specific domain d (with $d = 1, \dots, D$) is measured by an unobserved (latent) variable denoted by I_i^d. Instead one observes a set of K ordered categorical indicators Y_k^d, taking $m = 1, \dots, M$ 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}. $\widetilde{Y}_{ki}^d$ 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 $\boldsymbol{x}$ (that means that I_i^d is also a function of $\boldsymbol{x}$). This yields:

$$\begin{aligned} \widetilde{Y}_{1i}^d &= \beta_1 I_i^d(\boldsymbol{x}) + \boldsymbol{x}'_i \boldsymbol{\gamma}_1 + \epsilon_{1i} \\ \vdots \quad & \vdots \\ \widetilde{Y}_{Ki}^d &= \beta_K I_i^d(\boldsymbol{x}) + \boldsymbol{x}'_i \boldsymbol{\gamma}_K + \epsilon_{Ki} \end{aligned} \tag{1}$$

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_i^d and a measurement error which is the result of observable ($\boldsymbol{x}$) and unobservable characteristics. Thus the parameters $\boldsymbol{\gamma}_k$ 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:

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

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

$$\begin{aligned} \widetilde{Y}^d_{1i} &= \boldsymbol{x}'_i \boldsymbol{\gamma}_1 + \eta_{1i} \\ \vdots \;\; & \;\; \vdots \\ \widetilde{Y}^d_{Ki} &= \boldsymbol{x}'_i \boldsymbol{\gamma}_K + \eta_{Ki} \end{aligned} \tag{3}$$

where $\boldsymbol{\gamma}_k$ 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 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 each other through I^d, then they would be independent since 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 testing 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, jointly related through a set of parameters that capture residual unobserved heterogeneity. Details on this model are reported in online Appendix A (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 $Y_1^d, \ldots, Y_K^d$ 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 the Appendix A) in order to explore the existence of potential residual association due to unobserved factors. This 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 $Y_1^d, \ldots, Y_K^d$, 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 $\mathbf{B_{K-1}}$ 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 bivariate 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 to say that 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 a LR statistics among the $\mathbf{B}$ models and the $\mathbf{P}$ 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 extend model $\mathbf{E}$ which takes into account two potential effects of $\boldsymbol{x}$ on the joint distribution of $Y_1, \ldots, Y_K$. The first effect derives by relaxing the parallel lines assumption (see e.g. Williams, 2006), which assumes that the βs do not differ across categories of Y_k. The second is on the interaction terms so that we allow the latter to depend on $\boldsymbol{x}$. In particular we estimate $\mathbf{E}$, an *extended model* to evaluate whether the covariates, in addition to affect the marginal distribution of the responses, have also 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 each other.

[2]Notice that the independent model $\mathbf{B_1}$ is simply model $\mathbf{B_2}$ where the bivariate interaction terms are set to zero.

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., Niehues, 2014; Gimpelson and Treisman, 2015; Brunori 2016; Corneo and Grüner, 2000; Suhrcke, 2001, Kuhn, 2011). 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, United Kingdom, United States.[3]

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.

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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 to 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. Though 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 in 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 societies (more equal).

We construct 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

[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.

[4]In the pertinent ISSP Survey, most indicators in Table 1 range between 3 and 5 categories except *logdif*, *gtframe*, *unlegit* and *fairframe* whose construction is described in this Section.

she perceives a more unequal society with a small elite at the top, very few people in the middle and the great mass or the most of people at the bottom.

The last three indicators of the domain "Inequality of Outcome", *conflict*, *conflictr*, *conflictm*, correspond to three questions that ask the respondent' opinion about the existence, in his 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 the 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*), parent's education (*pedu*) and hard work (*pwork*). All questions have a 5-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", 2 if he answers "very important" or "essential". For the last one, *pwork*, the order is inverted since, as explained in Brunori (2016), it corresponds to a question about the role of effort and choice in determining success against the others that focus on circumstances beyond individual control.[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 health care than people with lower incomes?". As above, for these 5-point scale questions, we construct indicators that take 0 if the respondent answers "Very just, definitely right" or "Somewhat just, right", 1 if he answers "Neither just nor unjust, mixed feelings", 2 if he answers 'Somewhat unjust, wrong" or "Very unjust, definitely wrong".

The indicator *difinc* derives from the following question: "Differences in income are too large". The question ranges on a 5-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"), 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

[5]The original indicator has four categories. To create a three categories variable, we collapse the two highest categories in one.

[6]Although the relevant ISSP module includes further questions on the perceived distribution of opportunities but, 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.

perception of unfairness. Consider *unlegit* to start with. 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 *ought* to be like - which would you prefer for your country?". When the ratio takes value 0, it means that individuals think that their society is perfect as it is, when the difference is equal to 1 or 2, individuals think their society is increasingly more unequal than it should be. When the ratio takes a negative value, it 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 correspondent positive ones.

4.2. **Independent variables.** Independent variables are grouped in 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 in the top or 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. The 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 the online Appendix B, including the share of observation per country with respect to the entire sample from the ISSP dataset (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 inequality. The first area is concerned with the associations among indicators of perceived inequality, in particular,

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

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 cross-country. International comparisons provide a comparative assessment of the respondent's views that may be useful for policy purposes, especially if compared 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 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 between indicators.** Before modeling the joint distribution of the observable indicators $Y_1^d, \dots, Y_K^d$, 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 depends on the covariates reported in the online Appendix B and country dummies. We then test the null hypothesis of no residual association. Table 2 reports the values of the LR-test, which are asymptotically distributed as a χ^2 with 40 dof. For each domain the null hypothesis is rejected indicating that, conditional on observable covariates, indicators are not independent.

place table 2 here

Taking into account this residual source of association is crucial to evaluate the effect of covariates on the joint distribution of indicators. For instance, Figure 1 depicts the estimated Average Marginal Effects (AME) per country using model $\mathbf{B_1}$ and $\mathbf{B_2}$ respectively. A quick glance at the figure 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 domain, while much lower in the second domain.

This difference between model $\mathbf{B_1}$ and $\mathbf{B_2}$ indicates how important is to take into account residual correlation to evaluate how observable characteristics affect the joint distribution of indicators. Moreover, the existence of these correlations supports the idea that the indicators are jointly measuring a common unobservable phenomenon.

place figure 1 here

While model $\mathbf{B_2}$ assumes the existence of bivariate associations among indicators, our empirical strategy allows also 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 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 step and fit model $\mathbf{P_2}$: associations among indicators are now restricted not to vary across the responses' 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, results from the model with ($\mathbf{P_2}$) and without ($\mathbf{B_2}$) restrictions on the residual association parameters reported in Table 3 provide further information to the analysis of the association among 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 $\boldsymbol{P}_2$ in Table 3 reveal that they are positively associated but ignore the real structure of the association that can only be inferred when the base model $\mathbf{B_2}$ is estimated. Moreover, the association among 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).

place table 3 here

The second result on the association among indicators confirms the existence and relevance of multidimensionality. Rejecting the Plackett restrictions it can be noted that the size of associations changes non monotonically across response categories. In particular, bivariate associations in model $\mathbf{B_2}$ reveal the existence of a multidimensional underlying unobserved heterogeneity. In search for 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 domain (*unfaired* and *unfairheal*) with their respective confidence intervals.[8] In Figure 2 we observe that associations vary non monotonically across responses' categories. Not all indicators display the same behavior: some associations have a more linear trend, but a majority resembles the pattern in Figure 2,

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

unvealing the existence of a multidimensional underlying unobserved heterogeneity that systematically affects how respondents perceive inequality.[9]

place figure 2 here

To conclude, the possibility to destructure associations among indicators across categories reveals specific features of perceived inequality. Note that $\lambda_{2,2}$ is, with few exceptions, always positive and strongly significative. 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 is 7.07 times greater than the odds to report 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 next Sections, we explore how covariates affect perceived inequality.

5.2. **Cross-countries 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* $\mathbf{E}$ to allow the interaction terms (in our case, the bivariate associations of the base model $\mathbf{B_2}$) to depend on $\mathbf{x}$ and the βs 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 from model $\mathbf{E_2}$ the predicted probabilities among domains. 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.

place figure 3 here

Some observations are appropriate. First, the domain's ranges are quite different. Perceived inequality of outcomes ranges from 0.07 (Denmark) to 0.90 (South Korea); perceived inequality of opportunity from 0.03 (New Zealand) to 0.26 (Austria); perceived unfairness from 0.35 (New Zealand) to 0.80 (France). Differences in range come with different dispersion in terms of predicted probabilities. The latter is substantial for perceived inequality of outcomes 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

[9]The other figures are available upon request.

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

perception of inequality of outcomes and opportunity could also explains why, in the third domain, 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 (Alesina *et al.*, 2001; Alesina and La Ferrara, 2005; Corneo and Gruner, 2000; 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.

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 United States whereas, in Europe, it is so in France and Italy. Note also that the position that these four countries occupy in 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 perceived inequality of outcome and opportunity domains we display the distance between perceptions and the objective level of inequality in Figure 4.

place figure 4 here

The first observation is that respondents in the United States, Great Britain, Australia and New Zealand underestimate the objective level of inequality of outcome whereas in Germany, Italy, France, Sweden and Finland overestimate it. This result is in line with Niehues (2014) who predicts that American 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 preference for political party that favor the overhaul of the political establishment.

The second observation concerns inequality of opportunity for which three clusters of countries can be identified. Mediterranean countries like Spain, Italy and Portugal have the highest level of objective inequality of opportunity and perceptions are close to reality

[11]Brunori *et al.*, 2013 offer an overview on the studies that measure inequality of opportunity indexes. Most of them focus on specific countries like the United States or on restricted samples like 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.

– Spanishes and Portugueses slightly underestimate it while Italians overestimate it. Respondents in another group of countries, markedly Germany, United States, Australia and Switzerland, tend to overestimate the distribution of opportunities, whereas respondents in all the remaining countries – the majority in our sample – underestimate it.

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]

5.3.1. *Covariates.* Table 4 reports the AME for each domain when 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 one and a value equal to two for the independent (first and second column) and the multivariate model (third and fourth column). To start with, consider the domain 'Inequality of Outcome'. Respondents with intermediate and high incomes, with a middle or top class social position and very religious jointly report lower levels of perceived inequality. The results on income and self-positioning confirm the findings in 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 that tends to consider younger people as more adverse to inequality while the second is in line (Alesina and Giuliano, 2009).

The difference between Model $\mathbf{B_1}$ and $\mathbf{E_2}$ can be relevant. For instance, consider how *toppos* affects the probability of reporting a value greater than one in the domain of inequality of outcome. The difference between coefficients in Model $\mathbf{B_1}$ and $\mathbf{E_2}$ is about 20 per cent, 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 respondents. Respondents with intermediate or high levels of education perceive less inequality of opportunity, though education has no effect on perceived inequality of outcome. This confirms the finding in Alesina and Giuliano (2009). Note that, contrary to Brunori (2016), we do not observe any effect of experience of social mobility on perceived inequality of opportunity. If combined with the behavioural assumptions to study 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,

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

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.

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 in Andreoni and Vesterlund (2001) and Alesina and Giuliano (2009). Moreover, educated people perceive less unfairness than uneducated. Finally we find support for the self-esteem bias theory (Miller and Ross, 1975): respondents that 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 that sheds light 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 the domain that 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 the hardest for white, low education, middle aged Americans (Case and Deaton, 2015; Milanovic, 2015). Information about their perception of inequality could help to identify which target policy should pursue, how to alleviate their suffering, and how to best tackle the issue of political legitimacy.

place table 4 here

5.3.2. *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, 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:

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

where $\overline{z}$ 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 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 model 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.

place table 5 here

The effect of covariates on their associations reveals a multi-faceted picture with substantial variation among indicators. As an example, consider *leftparty*, that is a covariate that reveals the respondent's political views. Left leaning respondents are 17 per cent more likely than right leaning to believe that parent's wealth is important for success, 16 per cent that political connections count, 26 per cent that gender is relevant, 8 per cent that parent's education is important, and they are also 14 per cent 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 say it differently, that political views are closely linked to the weight that a person attributes to structural circumstances (family wealth, gender, etc.) for achievements (Kluegel and Smith, 1986; Alesina and Giuliano, 2009, Alesina and Angeletos, 2005, Alesina and Fuchs-Schündeln, 2007; Benabou and Tirole, 2006)

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 per cent), gender (17 per cent), parents' education (8 per cent) are important to get ahead in life, while effort is not (10 per cent). 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 literature's claim.

Another variable that is often scrutinized in the literature is *mobdown*, that indicates if the respondent has a 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. Here we can further dig on this result using the marginal and conditional

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

survival functions. We find that individuals that experience a downward movement in the social ladder are 14 per cent more likely to believe that parent's wealth is important, 13 per cent that gender is important and 12 per cent that parents' education is important. However, the effect on the other indicators is not significative. Contrary to *leftparty*, personal experiences like 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 per cent) are important.

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 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 suspect of inconsistency and unveiled by our methodology is given by the variable *toppos* that captures if respondents place themselves in the top scale of the society. These individuals are less likely to believe that parent's wealth (28 per cent), political connection (23 per cent) and gender (12 per cent) are important. However, they are also more likely to consider parents' education 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 attention to respondents who believe that parent's wealth is important, top-positioning individuals are more than 25 per cent less likely to believe that political connections are important and 5 per cent 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 survival conditional estimates reveal that, among believers that parent's 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, the level of education, *highed*. Theoretical predictions about the effects of education on the 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 (Szirmai, 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 per cent less likely to report that political connections are important and 18 and 7 per cent, 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. Unobservable must be dealt within a model that allows associations among indicators to vary across responses' categories.

6. Conclusion

In this paper we have presented an empirical analysis of perceived inequality. We have proposed a novel approach that explicitly acknowledges the multidimensionality and essential contestedness of perceived inequality as well as its determinants. 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 noted, previous experiences of social mobility, political views, self-positioning in society, parent's wealth, education, as well as other subjective variables bear important consequences on the perception of inequality. As we have argued, if joined with appropriate behavioural 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.

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	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 rich people can buy better education than poor people?
Unfairness	unfairheal	Just/unjust rich people can buy better health care 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

Table 2. Comparison and evaluation of models

Inequality of Outcome				
Model	Log-likelihood	LR test	dof	p-value
$\mathbf{B_1}$	-57259.33	-	-	-
$\mathbf{B_2}$	-52312.95	9892.75	40	0.0000
$\mathbf{B_3}$	-52268.49	88.91	80	0.2320
$\mathbf{P_2}$	-52590.71	555.52	30	0.0000
$\mathbf{E_2}$	-51367.36	1891.19	392	0.0000
Inequality of Opportunity				
Model	Log-likelihood	LR test	dof	p-value
$\mathbf{B_1}$	-63948.54	-	-	-
$\mathbf{B_2}$	-63948.54	6610.43	40	0.0000
$\mathbf{B_3}$	-63900.48	96.13	80	0.1056
$\mathbf{P_2}$	-64139.39	381.69	30	0.0000
$\mathbf{E_2}$	-63188.88	1519.32	392	0.0000
Perceived Unfairness				
Model	Log-likelihood	LR test	dof	p-value
$\mathbf{B_1}$	-59075.74	-	-	-
$\mathbf{B_2}$	-54504.81	9141.86	40	0.0000
$\mathbf{B_3}$	-54463.38	82.85	80	0.3917
$\mathbf{P_2}$	-54868.18	726.76	30	0.0000
$\mathbf{E_2}$	-53725.14	1559.33	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 $\mathbf{E_2}$.

TABLE 3. Estimated global log-odds ratio $\boldsymbol{\lambda}^a$ parameters for model $\mathbf{B_2}$

	conflictm conflictr	conflictm conflict	conflictm logdif	conflictm gtframe	conflictr conflict	conflictr logdif	conflictr gtframe	conflict logdif	conflict gtframe	logdif gtframe
Model $\boldsymbol{B}_2$										
$\lambda_{1,1}$	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 $\boldsymbol{P}_2$										
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 $\boldsymbol{B}_2$										
$\lambda_{1,1}$	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
Model $\boldsymbol{P}_2$										
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 $\boldsymbol{B}_2$										
$\lambda_{1,1}$	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 $\boldsymbol{P}_2$										
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

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

TABLE 4. Average Marginal Effect

	Inequality of Outcome				Inequality of Opportunity				Perceived Unfairness			
	ModelB_1		Model E_2		ModelB_1		Model E_2		ModelB_1		Model E_2	
var	$\Pr(\boldsymbol{Y} \geq 1)$	$Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$	$\Pr(\boldsymbol{Y} \geq 1)$	$\Pr(\boldsymbol{Y} \geq 2)$
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

Bootstraped standard errors are based on 1000 repetitions.
Countries dummies are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Survival and conditional survival function 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

y_j is the base indicator for the domain "Inequality of opportunity" that corresponds to wfam.
Bootstraped standard errors are based on 1000 repetitions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 1. AME per country for independent and multivariate model

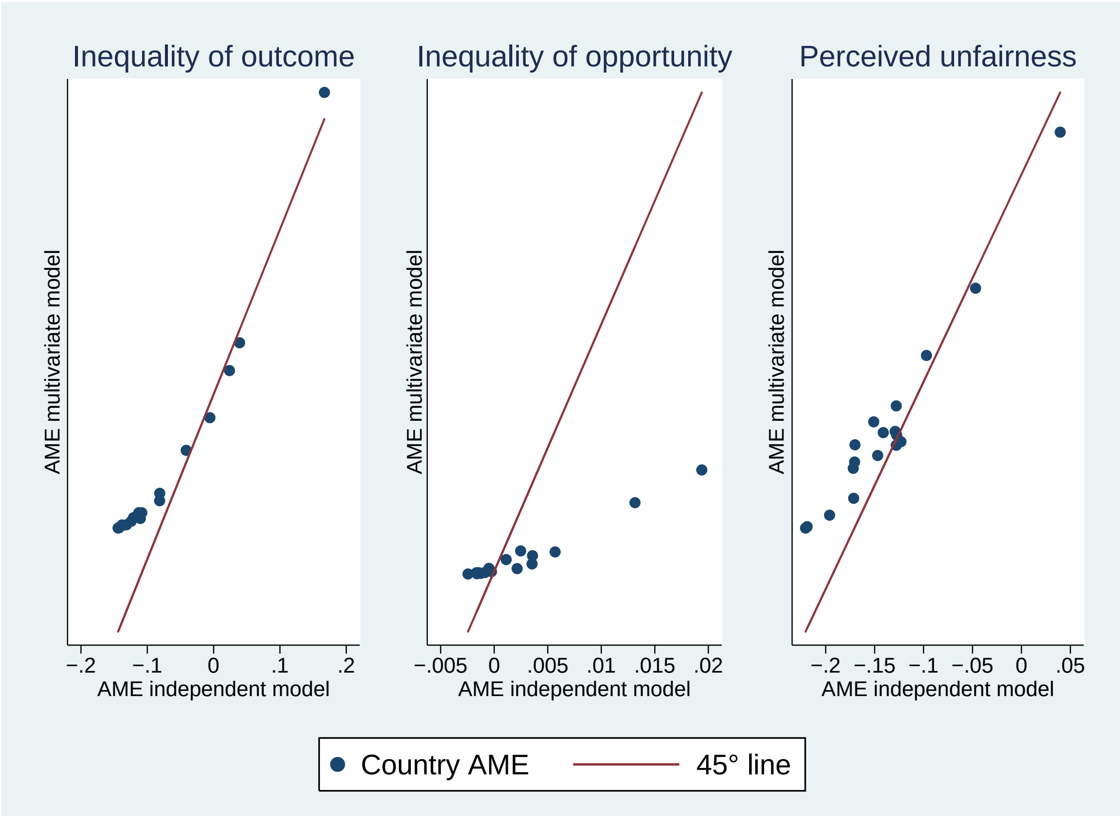


FIGURE 2. Global log-odds among two indicators in the same domain with confidence intervals

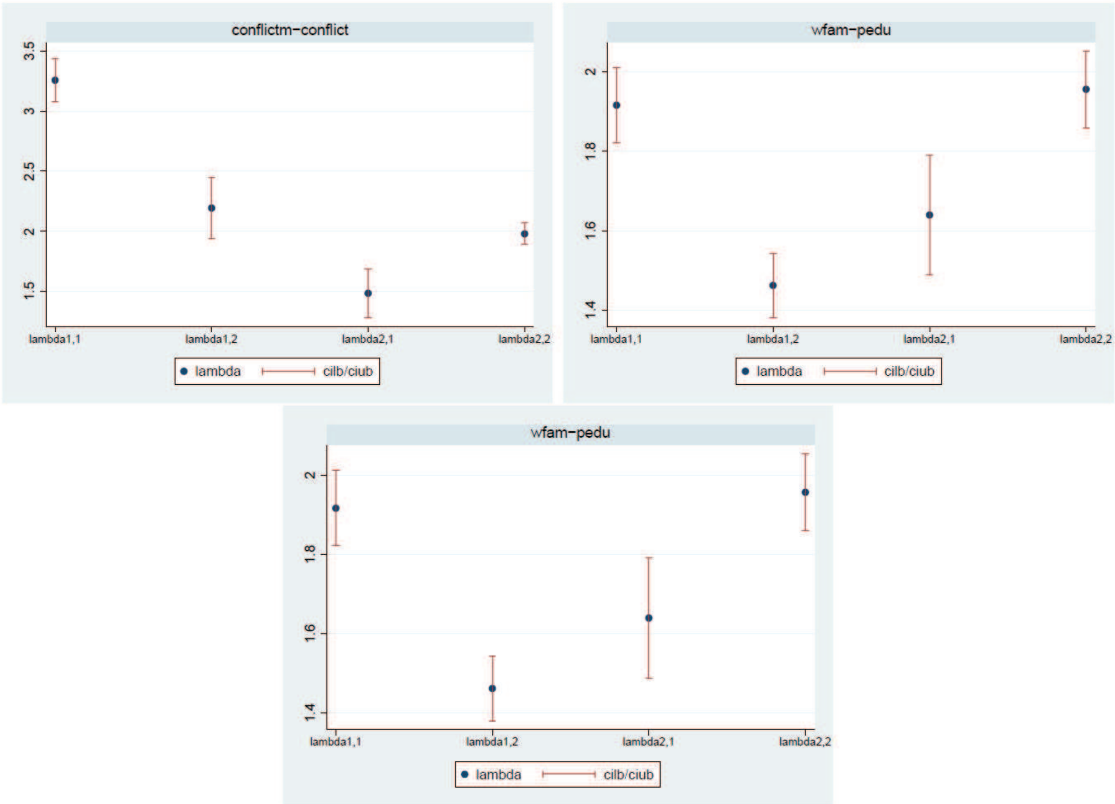


FIGURE 3. Countries with the highest level of perception in inequality and Unfairness with 95% confidence intervals

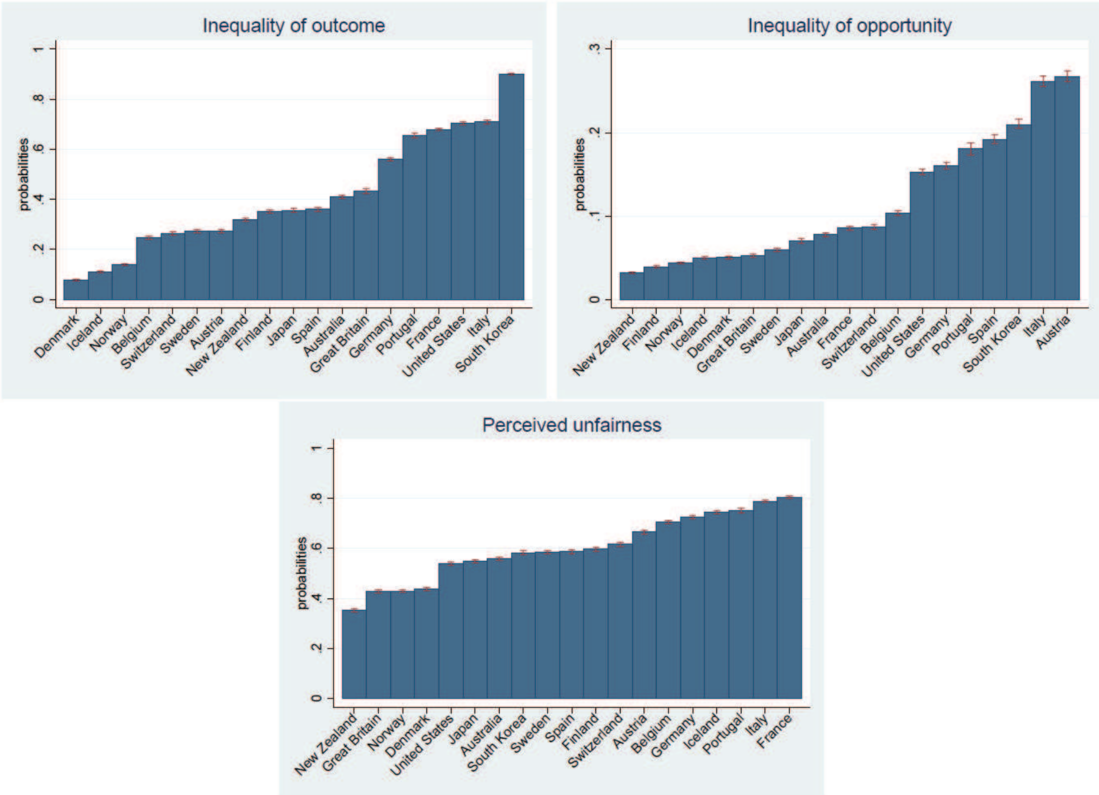
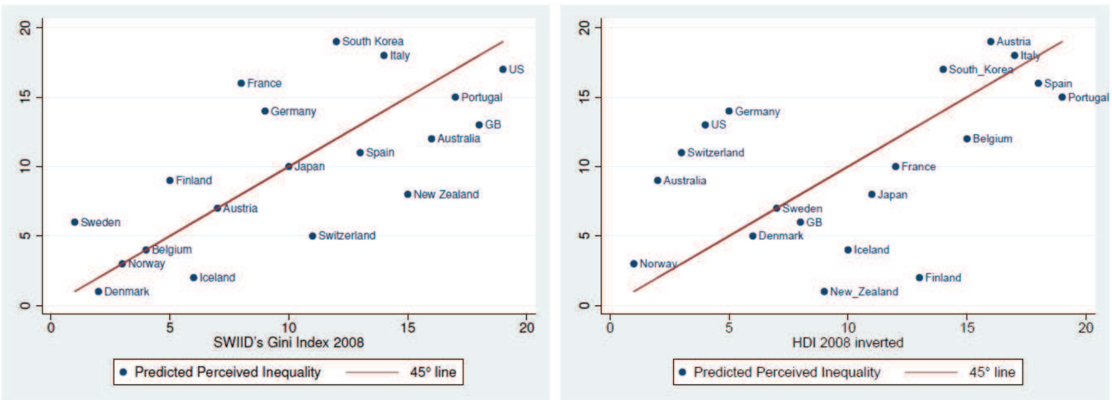


FIGURE 4. Perceived and Objective Inequality (rank)



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