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(Article begins on next page)

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Attitudes towards Roma people and migrants: a comparison through a Bayesian multidimensional IRT model

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Abstract

In the context of social psychological research on relations between cultural defined groups, the main topics of interest include ethnic prejudice, attitudes and stereotypes. In the present study, in order to measure and compare attitudes towards Roma people and migrants and to investigate how these attitudes vary according to individual characteristics, we develop an integrated model which embeds a multidimensional Item Response Theory model for polytomous data into a structural equation formulation. Item and person parameters and structural coefficients are estimated on data collected through a web survey. Full probabilistic inference is performed by applying Markov chain Monte Carlo techniques.

Introduction

According to Berry's model (Berry 2004) there are two distinct, but inter-related domains of psychological research that make up the field of group relations. When the groups involved are essentially cultural in nature, these two domains can be termed acculturation and ethnic relations. On the one hand, acculturation, seen as the dual process of cultural and psychological change that takes place as a result of contact between different cultural groups and their individual members (Berry 2006), has become a major focus of cross-cultural psychology. On the other hand, ethnic relations are investigated in the framework of social psychological research on intergroup relations, and the topics of interest include ethnic prejudice, attitudes, and stereotypes.

In this paper, we measure and compare attitudes towards Roma[1] and migrants by analyzing the dimensions of prejudicial predisposition and social acceptance, and by investigating how these attitudes vary according to individual characteristics and beliefs.

Given data collected using a web survey, in order to obtain a measure of the investigated attitudes, we use an Item response theory (IRT) model. IRT, also known as latent trait analysis (Lazarsfeld and Henry 1968), provides a class of models aimed to measure not directly observable variables in a rigorous way (de Ayala 2009). These models, initially developed as methods for the analysis of educational tests, have been extensively employed in many research fields including psychology and sociology, where applications deal primarily with attitudinal data.

In our research, since we define multiple latent variables, we consider a multidimensional version of the graded response model (Samejima 1969), developed in a Bayesian framework (de Jong and Steenkamp 2010). Furthermore, in order to study the relationships between the measured attitudes

and a set of explanatory variables, the IRT model is formulated within a structural equation framework.

IRT applications for measuring ethnic prejudice can be found in Reyna et al. (2013) and Rojas et al. (2011), where the rating scale formulation (Wright and Masters 1982) is used. A structural equation multi-group model is implemented in Pérez et al. (2014), with the aim of investigating the relationships between acculturation attitudes and some psychosocial variables including prejudiced attitude.

The remainder of this paper is structured as follows. In Sect. 2 we provide a review of relevant theories regarding the concepts of prejudice and stereotype. Section 3 is devoted to illustrate the research design. In particular, in this section we better clarify the aims of the study and illustrate the confirmatory model of our analysis. In Sect. 4 we present the methodology adopted and the estimation procedure. The description of the data collection process and of the sample composition is presented in Sect. 5, while the main results are described in Sect. 6. Finally, conclusions are given in Sect. 7.

Prejudice and stereotypes

Social psychology has often focused on the study of prejudice and stereotypes as phenomena of intergroup relations. In fact, we define prejudice as a negative evaluation of a social group, or a negative evaluation of an individual that is significantly based on the individual's group membership (Brown 2010). This simple definition takes us back to the complexity of this phenomenon: depending on the degree of specificity or generality we actually assume, there can be different facets. On the one hand, reference can be made to the term's etymological meaning, which comprises a judgement prior to the experience, we can apply to facts, events, interpersonal relations, social groups; on the other hand, at a more specific level, we can see prejudice as a tendency to consider a given social group in an unfavorable way (Brown 2010). These two levels have in common the fact that prejudice is not only an evaluation, but it concretely orients people's actions and behaviors, which can range from simply bearing in mind negative information on a certain group, or expressing one's own contrary opinions, or taking part in actions of overt violence against the persons who belong to that given group (Villano 2013b).

The term is thus imbued with a strongly negative significance. Its most common use concerns the hostility towards ethnic groups that are different from one's own, or towards minorities of various types. But also in daily life, in interpersonal relations, in judgements that are expressed in everyday discourse, it is considered to be right and desirable to be able to evaluate matters in an "objective" way, indeed free from prejudice. According to Reicher (2012) there are at least four basic assumptions of prejudice, that are: (1) prejudice is addressed to an outgroup; (2) it concerns *perceptions* in regard to that group;(3) it regards the *negative qualities* perceived in respect to that outgroup; (4) prejudice involves normal people who perceive the negative qualities of an outgroup.

Allport, in his text *The nature of prejudice* (1954), already stated that ethnic prejudice is an antipathy founded on a false and inflexible generalization, internally felt or expressed, directed towards a group as a whole or towards an individual as a member of that group. This antipathy is perceived as a generalization, which involves whole social categories (Voci and Pagotto 2010). The definition of "false and inflexible", that Allport attributes to the

generalization on which prejudice is based, derives from the unlikelihood that all the members share the same social categories, or that they are bearers of characteristics or values utilizable for a whole social category. It is also defined as inflexible as the real characteristics that belong to the individuals are ignored.

But which are the psychological processes that underlie the phenomena of stereotype and prejudice? Henri Tajfel, in his famous article *Cognitive aspects of prejudice* (1969), argued that the social changes, that occur during intergroup relations, depend continuously on the way in which people attribute a meaning, interpret and understand what is being modified. In other words, we understand and interpret the changes in our existence through some fundamental cognitive processes, such as the categorization, the assimilation and the search for coherence. In particular, categorization refers to the process according to which individuals mentally arrange their social world and reduce the quantity of information they have to deal with. It is seen as the process of arranging the environment in terms of categories, through which people, objects and similar or equivalent events are grouped on the grounds of their pertinence in respect to individual actions, intentions or attitudes.

The connection with stereotyping is inevitable. Researches have shown that stereotypes allow us to form an impression about an individual or a group without making any particular mental effort. Categorization and stereotypes have in common the fact that they are two cognitive mechanisms that lead to the simplification of the information and operate according to a process of mental economy. According to Tajfel (1969, p. 82) "the stereotypes are born from the process of categorization and produce simplicity and order where there is complexity and variation close to randomness. They can help us to manage complexity only if the blurred differences that are manifested between the groups are transformed into clear distinctions, or when new ones are created instead of non-existence differences".

Thus, the complexity of the world prevents us from preserving a differentiated attitude in respect to everything; the consequence is that we maximize our cognitive energy in order to develop accurate attitude only towards some issues, while we simplify our beliefs towards others. Given the limited human capacity to process information, people adopt shortcuts and practical rules to try to understand the others. Stereotypes and prejudice can be a ductile and economic way to deal with complex events to the extent that they are based on experience and are accurate. If, however, they conceal individual differences within a class of people, they become potentially damaging instruments.

The current trend of studies on prejudice is not only aimed to understand if this phenomenon exists: obviously it does, and we are all against it. Today the thorny question remains as to whether there is really equality (of opportunities) for everyone, and this issue leads us to look beyond, to speak of cultures—rigorously in the plural—to the inevitable differences, to the slippery boundaries but also to the psychological wealth that this involves. Prejudice should be seen and analyzed in a much broader way, not only as the perception of others, but above all as an element within the social relations that constitute our world.

Gallissot et al. (2001) identify prejudice as a cultural product. "It is the synthetic image that mediates our relationship with the real. Indeed, we perceive only what our culture has already elaborated for us: our vision of reality and our practical experience are formed within the contexts transmitted by our culture. (Stereotypes and prejudices) are an opinion (or better, a belief) without reasoning."

But if the use of categories to order the social world is an ordinary process of the human mind, in the case of stereotypes and prejudices we go beyond. Often the basic characteristics are extended in a way that brings together the members of a category with other requisites of a psychological type or pertaining to moral qualities or value judgements. The substantial difference makes use of categories as an ordinary instrument of classification of the world and their distorted utilization in the case of prejudices and stereotypes lies in the reason for which a given trait comes to be part of the category (Mazzara 1999). What happens, in other words, is an extension of the basic requisites that define the category and that pertain to social memberships, to requisites of a psychological type, regard the personality traits, the dispositions, the moral qualities. The complication lies in the fact that "most of the stereotypes are traits: hostile, dishonest, lazy, innocuous, stupid, and so on. If the stereotypes consisted only of easily measurable attributes, such as height and weight, the question of the evaluation, and the accuracy, would be simpler" (Fiske 2006, p. 183). The passage, that we often accomplish, is the connection between characteristics that in reality are not associated between them and for which a correspondence is established between a category and a particular disposition, to which we all too often add a value judgment and/or one of pleasantness. For example, we feel that Irene, being a woman, is also good at cooking and therefore reliable. Or that Vesna, a Roma girl, must be a thief. But what type of prejudice is the one towards the Roma people?

Gaertner and Dovidio (1986) argued that most people exhibit what they call "aversive racism", a style of prejudice that results (1) from prejudice that develops from historical and culturally racist contexts, and cognitive mechanisms that promote the development of stereotypes, and (2) from having an egalitarian value system. The prejudice that aversive racists feel is not open hostility, but rather discomfort, uneasiness.

Pettigrew and Meertens (1995, 2001) (Meertens and Pettigrew 1997) propose a theory of Western Europeans' prejudice that encompasses a range of ethnic groups, which they call subtle and blatant prejudice. They acknowledge the older, more fundamental, unrepressed blatant prejudice, and also "a more subtle form of outgroup prejudice [that] has emerged in recent years" (Pettigrew and Meertens 1995, p. 54). Blatant prejudice is characterized by perceived threats, of social, economic, and political nature, by outgroups, followed by rejection of outgroups as inferior and avoidance of contact with them. Defence of traditional values, exaggeration of cultural differences, and lack of positive emotion towards an outgroup are distinctive aspects of subtle prejudice.

If it is true that prejudice currently assumes subtle and hidden forms, which, however, do not diminish the pervasive form of this phenomenon, there is no doubt that prejudice towards the Roma people has been manifest in the past and still is today. A "historical" prejudice and almost "chronic", seeing that several Italians are still convinced that "Gypsies steal children" (Lerner 2007). But obviously not only Italians. On the eve of the last elections for the European Parliament, the results of a research conducted by Pew Research Center (Pew Research Center 2014) in different European countries, amongst which France, Greece, Germany, Italy, Poland and the United Kingdom, were published. The news date back to 14 May 2014 and the interesting part of the survey is the one referring to opinions on some ethnic groups, such as Muslims, Jews and Roma. No surprises: the most negative ones are on the Roma people. In Italy only 10 % declare they are in favor of this group, while 85 % have a negative opinion. This is followed by France (66 % against), Greece (53 %) and lastly Spain, with 41 %of people against: in other words, anti-Roma prejudice seems to constitute a pan-European phenomenon. With the figures to hand, the Roma people

continue to be a social problem, accused even today of being children snatchers, kidnappers, beggars. They are disconnected from any cultural circuit and the prejudices and stereotypes linked to them are deeply rooted and racist, overtly racist, seeing that the prejudice towards the Roma people is the only one to be ostentatiously open and manifest, direct and hostile towards this group. If indeed nowadays the trend is to conceal and hide the prejudices, those towards the Roma people are the only ones that remain unchanged and openly racist.

The research design and the confirmatory model

The aim of our analysis is to compare attitudes towards migrants and Roma and to investigate how those attitudes vary according to some individual characteristics and beliefs.

To investigate the degree of diffusion of prejudice and stereotypes, we developed a comprehensive questionnaire consisting of different item batteries. In this paper, attitudes towards immigration and the Roma people are compared by considering the dimensions of prejudicial predisposition and social acceptance. The latent concept of prejudicial predisposition is operationalized exploiting the semantic differential formulation (Osgood et al. 1957) which is a bipolar scale, defined with contrasting adjectives at each end. More specifically, prejudicial predisposition is measured by a 5-point semantic differential scale consisting of four items. Both for immigration and Roma we used the following pairs of polar adjectives: 'good–bad', 'attractive–unattractive'. In addition, for immigration we considered: 'positive–negative', 'valuable–valueless'; for Roma the added adjectives were 'active–passive', 'calm–agitated'. Social acceptance is detected through a Guttman scale (Guttman 1950), formulated following the pattern of the social distance scale proposed by Bogardus (1933), which measures people's willingness to participate in social contacts of varying degrees of closeness with members of diverse social groups. In particular, the level of closeness is assessed by considering the extent to which the respondent would accept an immigrant or a Rom as guest, neighbor, friend, fiance. An affirmative answer indicates complete acceptance, a doubtful answer partial acceptance, a negative answer rejection. Since the responses are coded such that a lower value corresponds to a positive answer and a higher value to a negative one, the latent variable can be interpreted as 'social distance'.

As individual characteristics we consider both some observed socio-economic variables and a latent variable representing national identity. The socio-economic explanatory variables are: age, gender, territorial area of residence, level of education, position on the left–right political spectrum, subjective assessment of the respondent's economic situation. The person's identity and sense of belonging to the Italian nation is operationalized through the following items : 'Being Italian is very important to me'; 'I identify myself as Italian'; 'I am very proud to be Italian'; 'I often regret being an Italian'; 'Being Italian reflects very well my personality'. The level of agreement or disagreement with each item is expressed on a 4-point Likert scale. In addition, we also take into account the respondent's perception of the Romani community's size in their city.

Following a confirmatory approach, our analysis is cast in the framework of structural equation models (Bollen 1989), where the latent dimensions linked to the attitudes towards immigration and the Roma people are assumed endogenous, while both observed and latent explanatory variables are assumed exogenous. The confirmatory model is represented in Fig. 1 using the path diagram. Here, for readability reasons, all the observed explanatory variables are

placed together in the same rectangle and the double-headed arrows between endogenous latent variables, indicating correlations, have been suppressed.

Fig. 1
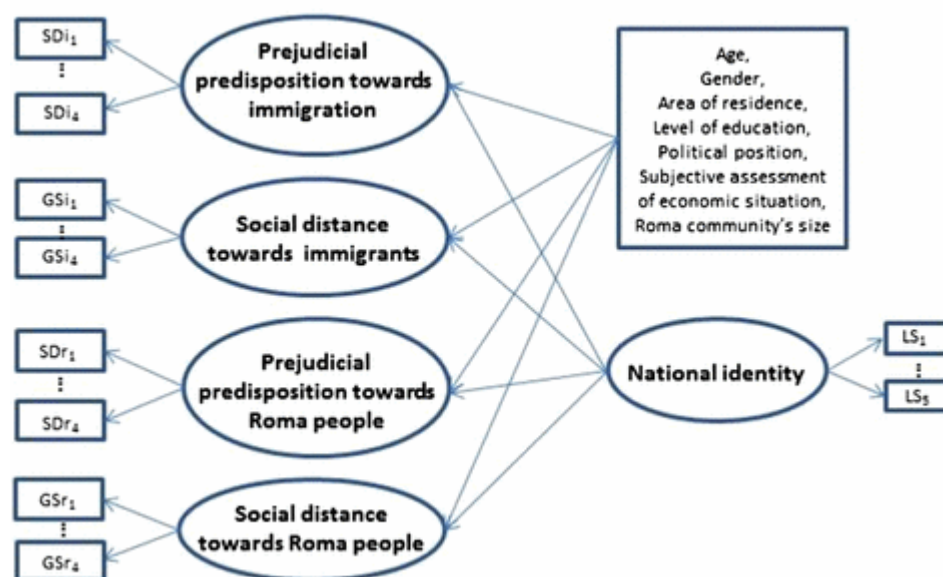
Path diagram (the acronym indicates which scale the indicator is referred to; *SD* semantic differential, *GS* Guttman scale, *LS* Likert scale—the subscript 'r' or 'i' indicates wether the indicator refers to Roma or migrants)

For the estimation of both the latent variable scores and the regression coefficients of the endogenous latent factors on the explanatory variables, a structural equation model (SEM) formulation for the graded response model for polytomous data is adopted. The statistical model is presented in Sect. 4 and the results are given in Sect. 6.

Methodology: SEM framework for multidimensional IRT models for polytomous response data

Item response theory models are stochastic models for the responses of persons to items, where the influence of items and persons on the responses are modeled by disjunct sets of parameters. From the IRT perspective, several models have been developed over the years, differing from each other in terms of item characteristics or parameters that are included in the model (they might range from 1-parameter to 3-parameter models) and in terms of response option format. In this latter respect, there are models designed to be used for binary outcomes and models intended to analyze polytomous data. Furthermore, when all the test items measure the same latent trait, unidimensional IRT models can be applied. On the other hand, when it is a priori clear that multiple latent traits are being measured, multidimensional IRT (MIRT) models have to be considered. MIRT is closely related to factor analysis despite the different focuses of the two approaches (Reckase 1997). More specifically, the unidimensional IRT model is appropriate when only one factor is extracted from the test items, whereas MIRT models are adopted when more than one factor are found to be significant. A useful distinction among MIRT model types was made

by Adams et al. (1997) who distinguished between-item and within-item multidimensionality. Between item multidimensionality occurs when items display an independent clustering solution with each item measuring only one construct, but the constructs being measured could be correlated to one another. This case, which can be thought of as a multi-unidimensional model (Sheng and Wikle 2007), is strictly linked to confirmatory factor analysis, where it is known a-priori that each latent trait is measured by a single sub-scale. Within-item multidimensionality occurs when individual items measure more than one latent construct. The classical multidimensional IRT models (Béguin and Glas 2001), where each item may potentially load on all the latent trait, can be considered both in an explanatory and a confirmatory perspective. With the use of Bayesian estimation procedures, different multidimensional models involving continuous latent traits have been developed (see, among others, Béguin and Glas 2001; Sheng and Wikle 2007, 2008; de Jong and Steenkamp 2010).

In this paper, in order to estimate prejudicial predisposition and social distance scores, given the confirmatory approach outlined in Sect. 3, we consider a multi-unidimensional model. Furthermore, since the indicators of those latent constructs are polytomous, we adopt the multidimensional normal ogive model (de Jong and Steenkamp 2010), which is a multidimensional version of the graded response model developed by Samejima (1969). For the exogenous latent variable 'national identity', measured by indicators evaluated on a 4-point Likert scale, we consider a unidimensional ogive model. The MIRT formulations of the unidimensional and multidimensional graded response models are presented in Sect. 4.2. To take into account the dependency of the endogenous latent variable on the exogenous latent variable and on the observed explanatory variables, we recast the IRT models within the SEM framework and the corresponding formulation is discussed in Sect. 4.1.

For the estimation of person and item parameters and of the regression coefficients, we adopt a fully Bayesian approach, using Markov chain Monte Carlo (MCMC) simulation techniques, which are extremely general and flexible. The details of the simulation procedure are given in the Appendix.

Structural equation formulation

If we are interested in investigating the relationships existing between M constructs, measured by K observed items, and a set of observed and/or latent covariates, the IRT model can be cast in the framework of structural equation models (SEMs), which comprise two components: a measurement model and a structural model. The measurement model relates observed responses to latent variables. The structural model specifies relations among latent variables and regressions of latent variables on observed variables. When the indicators are categorical, the conventional measurement model for continuous variables needs to be modified and the structural equation formulation is extended to generalized latent variable models (Skrondal and Rabe-Hesketh 2004), where, conditional on the latent variables, the measurement equation is a generalized linear model which can be used for a much wider range of response types.

We assume that there is a linear relationship between the endogenous latent variables $\boldsymbol{\theta} = \{\theta_1, \theta_2, \theta_3, \theta_4\}$, representing prejudicial predisposition and social distance scores towards migrants and the Roma people, and the exogenous latent variable 'national identity', denoted by ξ, and measured by $J = 5$ categorical indicators. In addition, we consider that $\boldsymbol{\theta}$ depends linearly on a set of observed covariates $\boldsymbol{w}$. Therefore, the structural model for subject $i = 1, ..., N$, can be expressed as

$$\boldsymbol{\theta}_i = \boldsymbol{\beta}_0 + \boldsymbol{\beta_1}\xi_i + \boldsymbol{\Upsilon}\boldsymbol{w}_i + \boldsymbol{u}_i = \boldsymbol{B}\boldsymbol{d}_i + \boldsymbol{u}_i$$

(1)

Here, $\boldsymbol{\theta}_i$ is a M-dimensional ($M = 4$) vector of latent variable scores, $\boldsymbol{d}_i = [1\ \xi_i\ w$ $w_i']'$ is P-dimensional ($P = 10$) vector containing both the observed values of the explanatory variables, $\boldsymbol{w}_i$, and the score of the exogenous latent factor, ξ_i; $\boldsymbol{B} = [\beta$ $\boldsymbol{\beta}_0\ \boldsymbol{\beta_1}\ \boldsymbol{\Upsilon}]$ is a ($M \times P$) matrix of structural parameters, where $\boldsymbol{\beta}_0$ represents an intercept vector, $\boldsymbol{\beta}_1$ contains the coefficients of the regression of the dependent latent constructs on national identity, and $\boldsymbol{\Upsilon}$ is the matrix of the regression coefficients of $\boldsymbol{\theta}$ on the observed socio-economic variables; $\boldsymbol{u}_i$ is a vector of disturbances, typically multivariate normal with zero mean.

Since the indicators of both the endogenous and the exogenous latent variables are categorical, the measurement models can be specified for the underlying continuous responses x^* and $\boldsymbol{y}^*$

Here v_x and $\boldsymbol{v}_y$ represent the intercepts, α_x and $\boldsymbol{A}_y$ are the factor loadings, ϵ_x and $\boldsymbol{\epsilon}_y$ are the unique factors or measurement errors.

When ϵ_x is assumed to be normally distributed and $\boldsymbol{\epsilon}_y$ is multivariate normal, each of these measurement models, combined with the threshold model for subject i,

$$x_{ij} = c \ if \ \gamma_{j,c-1}^{(x)} \le x_{ij}^* \le \gamma_{j,c}^{(x)}, \quad for \ item \ j = 1, ..., J$$
$$y_{ik} = c \ if \ \gamma_{k,c-1}^{(y)} \le y_{ik}^* \le \gamma_{k,c}^{(y)}, \quad for \ item \ k = 1, ..., K$$

is a 2-PL normal ogive model (Skrondal and Rabe-Hesketh 2004). More specifically, Eq. (2) represents a unidimensional graded response model, while Eq. (3) is the multidimensional version of this model.

Unidimensional and multidimensional normal ogive models for polytomous data

In the graded response model (Samejima 1969), the probability that an individual i, given some underlying latent trait ξ_i, gives a response x_{ij}, falling into category c ($c = 1, ..., C_x$), on item j, may be expressed as follows:

$$Pr\left(X_{ij} = c \,|\, \xi_i, \alpha_j^{(x)}, \boldsymbol{\gamma}_j^{(x)}\right) = \Phi\left(\alpha_j^{(x)}\xi_i - \gamma_{j,c-1}^{(x)}\right) - \Phi\left(\alpha_j^{(x)}\xi_i - \gamma_{j,c}^{(x)}\right)$$

(4)

where $\Phi(\,\cdot\,)$ denotes the standard normal cumulative distribution function, $\alpha_j^{(x)}$ is the item discrimination parameter, and the category threshold parameters are ordered as follows: $-\infty < \gamma_{j,1}^{(x)} \le \cdots \le \gamma_{j,c}^{(x)} \le \cdots \le \gamma_{j,C_x-1}^{(x)} < \infty$.

Given M correlated constructs, measured by K observed categorical items, the multidimensional version of the graded response model is given by (Béguin and Glas 2001):

$$P\left(Y_{ik} = c \,\middle|\, \boldsymbol{\theta}_i, \boldsymbol{\alpha}_k^{(y)}, \boldsymbol{\gamma}_k^{(y)}\right) = \Phi\left(\sum_{m=1}^{M} \alpha_{k,m}^{(y)} \theta_{i,m} - \gamma_{k,c-1}^{(y)}\right) - \Phi\left(\sum_{m=1}^{M} \alpha_{k,m}^{(y)} \theta_{i,m} - \gamma_{k,c}^{(y)}\right)$$

(5)

In our confirmatory framework, we deal with a multi-unidimensional IRT model, therefore each item loads only onto a construct, i.e. each of the M correlated constructs is being measured by its own set Ω_m containing K_m items ($\sum_{m=1}^{M} K_m = K$). This assumption can be written as $\alpha_{k,m}^{(y)} \neq 0$ if $k \in \Omega_m$, $\alpha_{k,m}^{(y)} = 0$ if $k \notin \Omega_m$, and the matrix of discrimination parameter has a block structure.

Bayesian estimation of the model parameters

Considering the unidimensional and multidimensional normal ogive models, described in Sect. 4.2, we assume that the person parameters are independent and identically distributed samples from univariate or multivariate Gaussian distributions: $\xi_i \sim \mathcal{N}(\mu_\xi, \sigma_\xi^2)$ and $\boldsymbol{\theta}_i \sim \mathcal{N}_M(\boldsymbol{\mu}_\theta, \boldsymbol{\Sigma}_\theta)$ (Béguin and Glas 2001). Given the structural model in Eq. (1), we have $\boldsymbol{\mu}_\theta = \boldsymbol{B}\,\mathbf{d}_i$, and, therefore, $\boldsymbol{\theta}_i \sim \mathcal{N}_M(\boldsymbol{B}\,\mathbf{d}_i, \boldsymbol{\Sigma}_\theta)$.

The prior for μ_ξ is normal, $\mathcal{N}(\mu_{\xi_0}, \sigma_{\xi_0}^2)$, and we set the location hyper-parameter to zero ($\mu_{\xi_0} = 0$) and the scale to some large value ($\sigma_{\xi_0}^2 = 100$).

The regression coefficients are assumed to have a matrix variate normal distribution, $\boldsymbol{B} \sim \mathcal{MN}_{M \times P}(\boldsymbol{\mu}_{B_0}, \boldsymbol{V}_M, \boldsymbol{V}_P)$, which can be written as $vec(\boldsymbol{B}) \sim \mathcal{N}_{MP}(vec(\boldsymbol{\mu}_{B_0}), \boldsymbol{\Sigma}_{B_0} = \boldsymbol{V}_P \otimes \boldsymbol{V}_M)$ where $\otimes$ denotes the Kronecker product and vec is the vectorization of a matrix. We fix $vec(\boldsymbol{\mu}_{B_0}) = \mathbf{0}$ and $\boldsymbol{\Sigma}_{B_0} = \sigma_{B_0}^2 \mathbf{I}_{MP}$ with $\sigma_{B_0}^2 = 100$ and $\mathbf{I}_{MP}$ the identity matrix of order $M \cdot P$.

We consider a gamma prior for the precision of the latent trait ξ, $\sigma_\xi^{-2} \sim Ga(n_{\xi_0}, s_{\xi_0})$, where we fix $n_{\xi_0} = s_{\xi_0} = 0.01$. The prior for the inverse of the variance–covariance matrix of the latent traits $\boldsymbol{\theta}$ is a Wishart $\boldsymbol{\Sigma}_\theta^{-1} \sim Wish(M + 1, s_{\theta_0} \mathbf{I}_M)$ with scale matrix $0.1\mathbf{I}_M$ and degree of freedom $M + 1$.

On the item side, we assign a uniform prior to the ordered thresholds

$$\gamma_{j,c}^{(x)} \sim uniform, \ c = 1, \dots, C_x - 1, \ \gamma_{j,1}^{(x)} \leq \cdots \leq \gamma_{j,C_x-1}^{(x)}, \quad \forall j$$

$$\gamma_{k,c}^{(y)} \sim uniform, \ c = 1, \dots, C_y - 1, \ \gamma_{k,1}^{(y)} \leq \cdots \leq \gamma_{k,C_y-1}^{(y)}, \quad \forall k$$

and assume that all 'free' discrimination parameters are positive and follows a truncated normal distribution

$$\alpha_j^{(x)} \sim N(\mu_{\alpha_x}, \sigma_{\alpha_x}^2) I(\alpha_j^{(x)} > 0), \quad \forall j$$

$$\alpha_{k,m}^{(y)} \sim N(\mu_{\alpha_y}, \sigma_{\alpha_y}^2) I(\alpha_{k,m}^{(y)} > 0), \quad if \ k \in \Omega_m$$

where $I(\cdot)$ represents the indicator function. The means and the variances are fixed at 1 and 100, respectively. The assumption of positivity is linked to the fact that all items have the same direction.

The unidimensional and multidimensional graded response models need identification restrictions since they are over-parameterized. The nature of the rating scale implies that scale restrictions have to be imposed because the observed outcomes do not change for different combinations of parameters. The locations of the latent variables are influenced by the mean of the latent traits and the threshold parameters $\boldsymbol{\gamma}_k$. To fix the location indeterminacy we can impose a constraint on the mean of the latent traits (*i.e.* $\mu_\xi = 0$ and $\boldsymbol{\mu}_\theta = \mathbf{0}$) or on the thresholds. Following de Jong and Steenkamp (2010), for a chosen category c, we consider the constraints $\sum_{j=1}^J \gamma_{j,c}^{(x)} = 0$ and $\sum_{k \in \Omega_m} \gamma_{k,c}^{(y)} = 0$ for each dimension $m = 1, ..., M$. Analogously, the variances and covariances of the latent traits are determined both by the latent trait variance (σ_ξ^2) or covariance matrix ($\boldsymbol{\Sigma}_\theta$) and by the discrimination parameters. To solve this problem it is possible to restrain the scale of the latent traits, assuming that each latent component has unit variance, or we can set to 1 the discrimination parameter of a chosen item for each dimension or, finally, we can impose that across the items of each dimension, the product of the discrimination parameters is equal to 1 ($\prod_{j=1}^J \alpha_j^{(x)} = 1$ and $\prod_{k \in \Omega_m} \alpha_{k,m}^{(y)} = 1$).

In the MCMC estimation procedure, to draw samples from the conditional distribution of the parameters it is convenient to use data augmentation technique (Tanner and Wong 1987). For each observed polytomous item, we assume that a continuous variable z underlies the observed ordinal measure and that there is a linear relationships between the item and person parameters and the underlying variable such that $z_{i,k}^{(y)} = \boldsymbol{\alpha}_k'^{(y)} \boldsymbol{\theta}_i + e_{i,k}$, with $e_{i,k} \sim \mathcal{N}(0, 1)$. In a confirmatory approach, where each item loads only onto a latent dimension, the linear relation reduces to $z_{i,k}^{(y)} = \alpha_{k_m}^{(y)} \theta_{i_m} + e_{i,k}$ or in matrix formulation $\boldsymbol{z}_k^{(y)} = \alpha_{k_m}^{(y)} \boldsymbol{\theta}_m + \boldsymbol{e}_k$, $\boldsymbol{e}_k \sim \mathcal{N}_N(\mathbf{0}, \mathbf{I})$, where $\boldsymbol{z}_k^{(y)}$, $\boldsymbol{\theta}_m$ and $\boldsymbol{e}_k$ are N-dimensional vectors. The same relation is assumed for the exogenous latent variable ξ: $\boldsymbol{z}_j^{(x)} = \alpha_j^{(x)} \boldsymbol{\xi} + e$ e_j, $\boldsymbol{e}_j \sim \mathcal{N}_N(\mathbf{0}, \mathbf{I})$. The relation between the observed item and the underlying variable is expressed by the threshold model discussed in Sect. 4.1.

The full conditional of most parameters can be specified in closed form which allows for a Gibbs sampler although Metropolis–Hastings steps are required to sample the threshold parameters. In particular to simulate the thresholds we consider the Cowles' algorithm (Cowles 1996), which is a Metropolis–Hastings (MH) step that replaces the Gibbs sampling step for simulating the thresholds from uniform distributions. Rather than simulating the thresholds from narrow uniform distributions, Cowles' algorithm generates candidate thresholds over the entire interval between adjacent thresholds and then uses the standard MH accept/reject criterion for determining whether to accept the candidate.

Full details of the estimation procedure are given in the Appendix.

Data collection and sample composition

Data were collected by means of a web-based survey, which offers many advantages over traditional methods such as low costs, automation and real time access, rapid collection of data, absence of any interviewers. In particular, online surveys increase the distance between researcher and respondent leading to a reduction of social desirability bias in responses. The absence of an interviewer makes respondents more willing to share personal information and opinions as they are not revealing them directly to another person. A detailed illustration of

advantages and liabilities of online surveys is provided by van Selm and Jankowski (2006).

In our research, we gathered information through a non-probabilistic sampling procedure and the questionnaire was spread across different mailing lists and social networks for 15 days (from 20 november to 5 dicember 2013), reaching a total number of 530 persons. A socio-demographic set of questions was administered to participants in order to obtain information about gender, age, territorial area of residence, level of education, political orientation and self-assessment of economic situation. The data highlight that the majority of respondents are women (64 %) and have their residence in the Italian southern regions (69 %). Looking at the age distribution, we find that respondents are aged from 16 to 60 years (mean = 29; standard deviation = 7.6). There is a significant number of respondents in the class 20–35 years, and this concentration probably depends on a larger diffusion of social networks in that age group. The overall level of education is high: an important proportion (66 %) of respondents have attained a first level or second level degree. With regard to political orientation, 45 % of respondents are positioned on the left side of the political spectrum and 10 % on the right side. Within the total sample, the minority (40 %) are satisfied with their economic and financial situation.

Results of the SEM-MIRT model

In what follows, we provide the results of the model discussed in Sect. 4. The algorithm, for the MCMC simulations presented in the Appendix, has been programmed in MATLAB. For the fitted model, the MCMC algorithm was run for 120,000 iterations. Posterior inference was based on the last 100,000 draws using every 5th member of the chain to avoid autocorrelation within the sampled values. Convergence of the chains of the model was monitored visually through trace plots.

## Item and person parameter estimates in the unidimensional and multidimensional measurement models

As discussed in Sect. 3, we consider one independent latent variable, named 'national identity', and $M = 4$ dependent latent constructs, identified as 'prejudicial predisposition' and 'social distance' towards migrants and the Romani population.

In the unidimensional normal ogive model, given in Eq. (4), for the exogenous latent variable we consider $J = 5$ items measured on a 4-point Likert scale ($C_x = 4$). In order to have all the items measuring the concept in the same direction, the reponse categories for 'I often regret being an Italian' have been recoded in reverse order. Table 1 summarizes the main findings for the item parameters of the graded response model for the national identity construct, that is the posterior mean estimates, the standard deviation and the 90 % equal-tailed credible intervals (CI) for the discriminations $\alpha_j^{(x)}$, and thresholds $\boldsymbol{\gamma}_j^{(x)}$, for $j = 1$, ..., J. For identifiability purposes, the constraints $\prod_{j=1}^{J} \alpha_j^{(x)} = 1$ and $\sum_{j=1}^{J} \gamma_{j,2}^{(x)} = 0$, have been applied.

> **Table 1 National identity: posterior estimates of item parameters for the unidimensional graded response model**

On inspection of Table 1, we can notice that the less discriminative statements are 'I often regret being an Italian', and 'Being Italian reflects very well my personality', while the other items show similar discriminative capacity. The item thresholds estimates, displayed in Fig. 2, confirm a similar pattern for all the items of the 'national identity' scale.

Fig. 2

National Identity: threshold parameters
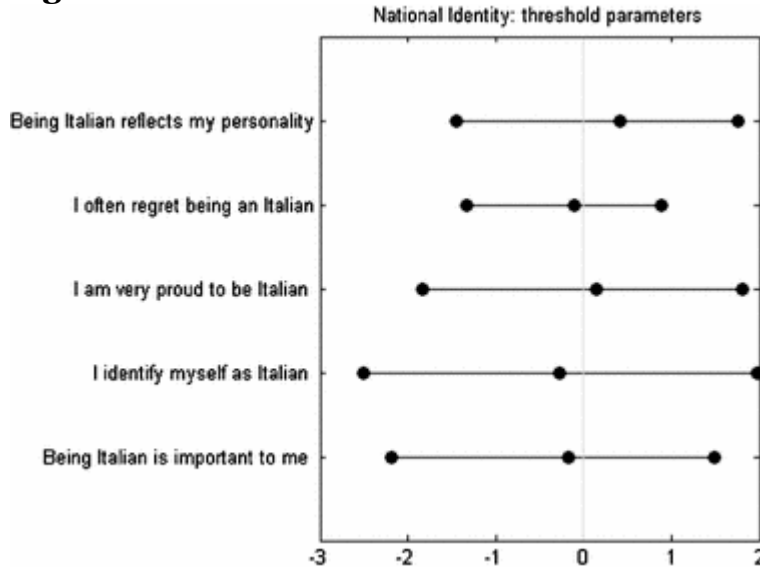
Item threshold posterior estimates for the latent dimension 'National identity'

In the multi-unidimensional measurement model, given in Eq. (5), each of the 4 endogenous latent variables is measured by 4 items, ($k_m = 4$, $m = 1, ..., M$; $K = \sum_{k=1}^{4} k_m = 16$). For each item, we consider 3 ordered categories ($C_y = 3$), since the responses to the 6-point semantic differential scales have been recoded into 3 categories. The location identifiability constraints, $\sum_{k \in \Omega_m} \gamma_{k,c}^{(y)} = 0$, for $m = 1, ..., M$, have been applied for $c = 1$. For the scale identifiability, we set the variance of the latent variables to 1. Table 2 summarizes the main findings for the item parameters of the multidimensional graded response model for prejudicial predisposition and social distance towards migrants and Roma.

Table 2 'Prejudicial predisposition' and 'Social distance' towards migrants and Roma people: posterior estimates of the item parameters of the graded response model

The discrimination parameters, displayed in Table 2, highlight that the most discriminative pairs of polar adjectives, measuring prejudicial predisposition towards immigration, are 'positive–negative' and 'good–bad'; while towards Roma we have 'good–bad' and 'attractive–unattractive'. It is worth noting that the discrimination parameter values are larger if we consider attitudes towards immigration. On the other hand, the most discriminative social distance scale items are 'neighbor' and 'friend', and their values are larger with regard to distance towards the Roma people.

The item thresholds estimates, displayed in Fig. 3, show how even respondents with a lower level of prejudice are more likely to characterize immigration as unattractive and worthless and Roma as agitated and passive. Regarding social

distance, the thresholds show the same pattern with respect to migrants and the Roma people. More specifically, even respondents with a higher level of acceptance are less prone to accept an immigrant and a Rom as a guest or a fiance.

Fig. 3
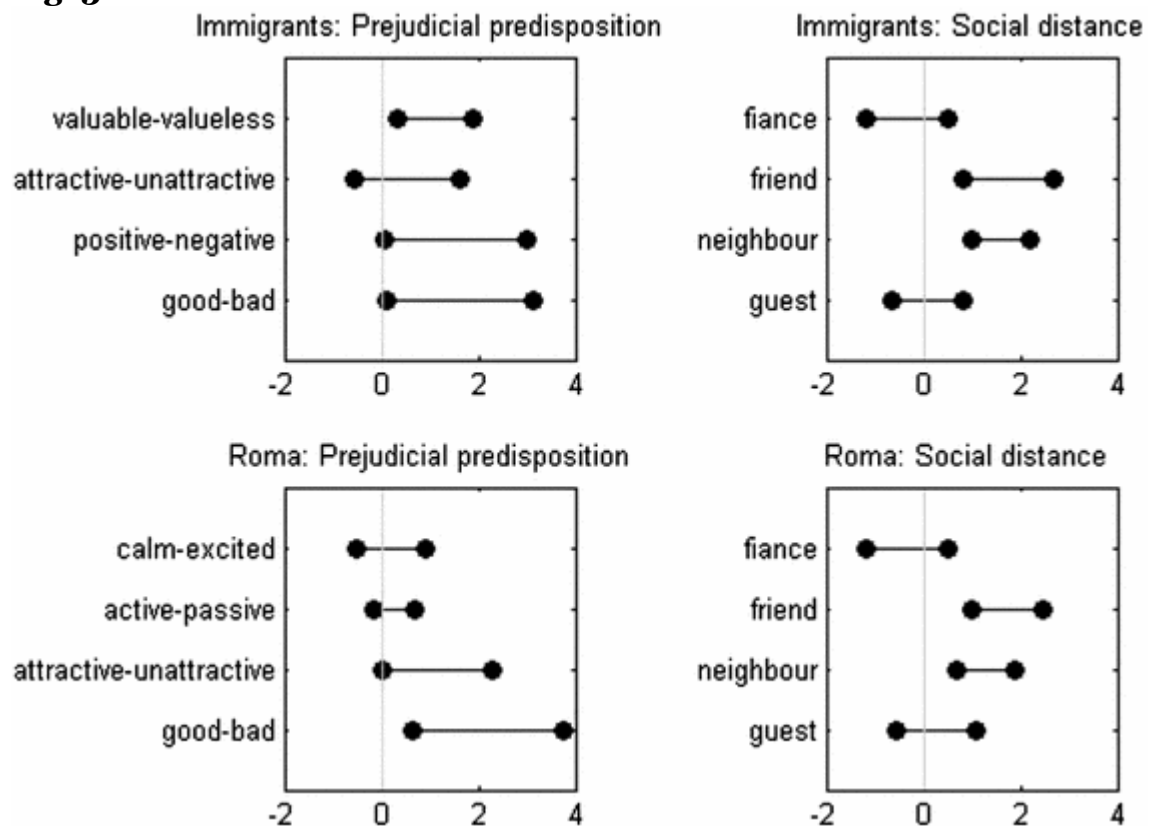
Item threshold posterior estimates for the latent dimensions 'Prejudicial predisposition' and 'Social distance' towards migrants and Roma

From the distributions of the person parameter estimates for the unidimensional and the multidimensional graded response models, represented in Fig. 4, it turns out a more unfavorable attitudes towards the Romani population. Boxplots clearly show that respondents have a more prejudicial predisposition and a lower level of closeness towards Roma.

Fig. 4
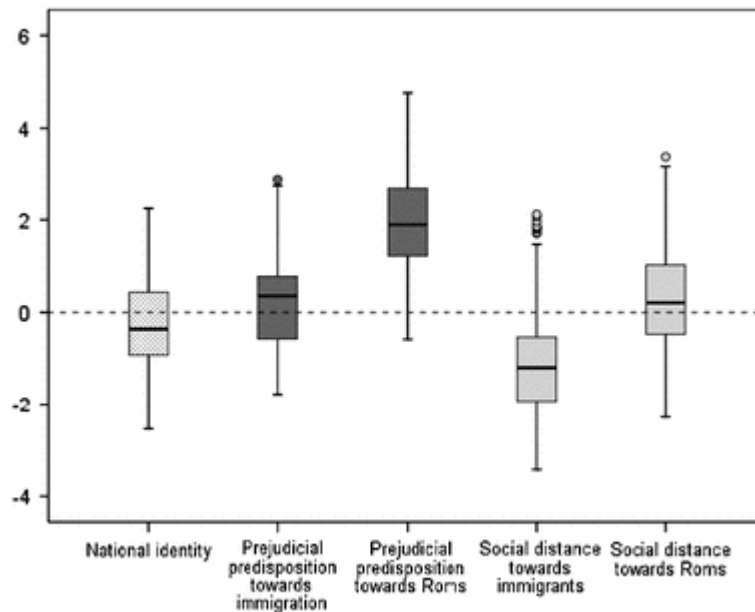
Person parameter posterior estimates for the latent dimensions
'National identity', 'Prejudicial predisposition' and 'Social distance'
towards migrants and Roma

The positive correlation coefficients between the endogenous latent variables
testify concordance in attitudes in terms of prejudice and refusal of close
relationships. The highest level of positive association is observed for prejudicial
predisposition and social distance in relation to the Roma people (Table 3).

**Table 3 Correlation coefficients and 95 % credible intervals
for the endogenous latent variables**

Estimated relationships for the structural model

Besides considering the comparison between attitudes towards Roma and
migrants, we aim to investigate how prejudicial predisposition and social
distance vary according to some individual characteristics and beliefs. As
explained in Sect. 3, as individual socio-economic aspects we consider age,
gender, territorial area of residence, level of education, position on the left–right
political spectrum and subjective assessment of the respondent's economic
situation. Age has been centered around the mean values of 29 years. For the
territorial area of residence we consider two categories: 'central and north Italy'
and 'south-Italy and islands'. Education has been recoded into two levels: 'below
the lower tertiary level' and 'lower tertiary education and above'. The placement
on the left–right political spectrum, observed on a 7-point scale, has been
recoded into three positions: 'left', 'center' and 'right'. The reference categories
for the dummy variables are: female; residence in southern Italy regions;
education below the lower tertiary level; placement on the central position;
unsatisfied with one's own economic situation. With regard to the question '*In
your opinion, is the Romani community in your city very large?*', we set as
reference category a positive answer.

In the model, we consider also the dependency of the endogenous latent
variables on the latent variable representing national identity of the
respondents.

The Bayesian estimates of the regression coefficients of the structural equation are displayed in Table 4. The significance of the coefficients has been derived according to Lindley's method for hypothesis testing in Bayesian framework (Thulin 2014). More specifically, the hypothesis that the regression coefficient is equal to 0 at the $(1 - a)100\%$ level of significance is rejected if the $(1 - a)100\%$ credible interval does not include 0.

Table 4 Posterior means of estimated regression coefficients

On inspection of Table 4, we see that data do not show enough evidence for the dependency of attitudes on age and satisfaction with economic condition. Considering the significant regression coefficients, we notice that respondents who have a greater sense of Italian national identity are more prone to show higher prejudicial predisposition and social distance towards both immigration and the Roma people. Male respondents disclose greater willingness to establish close relations with migrants, while interviewed from north-central Italy reveal a lower social distance towards Roma. Respondents with a higher level of education present a lower prejudicial attitude and social distance towards migrants but not with respect to Roma. The attitudes towards the Roma people worsen, if their community's size is perceived as large. Compared to respondents who place themselves on the central position of the left–right political spectrum, individuals who are on the left-wing side clearly show more positive attitudes, but the influence is larger for migrants than for the Roma people. On the contrary, respondents on the right side have a higher level of prejudicial predisposition and a lower degree of acceptance, and the strength of the influence of their political view is higher with respect to attitudes towards Roma. It is worth noting that, even if attitudes towards migrants and the Romani population are more positive for respondents who are positioned on the left, all respondent show a higher level of prejudicial predisposition and a higher social distance towards Roma people, as can be clearly seen in Fig. 5 where the latent variable scores are represented for each of the positions on the 7-point political scale considered in the questionnaire.

Fig. 5
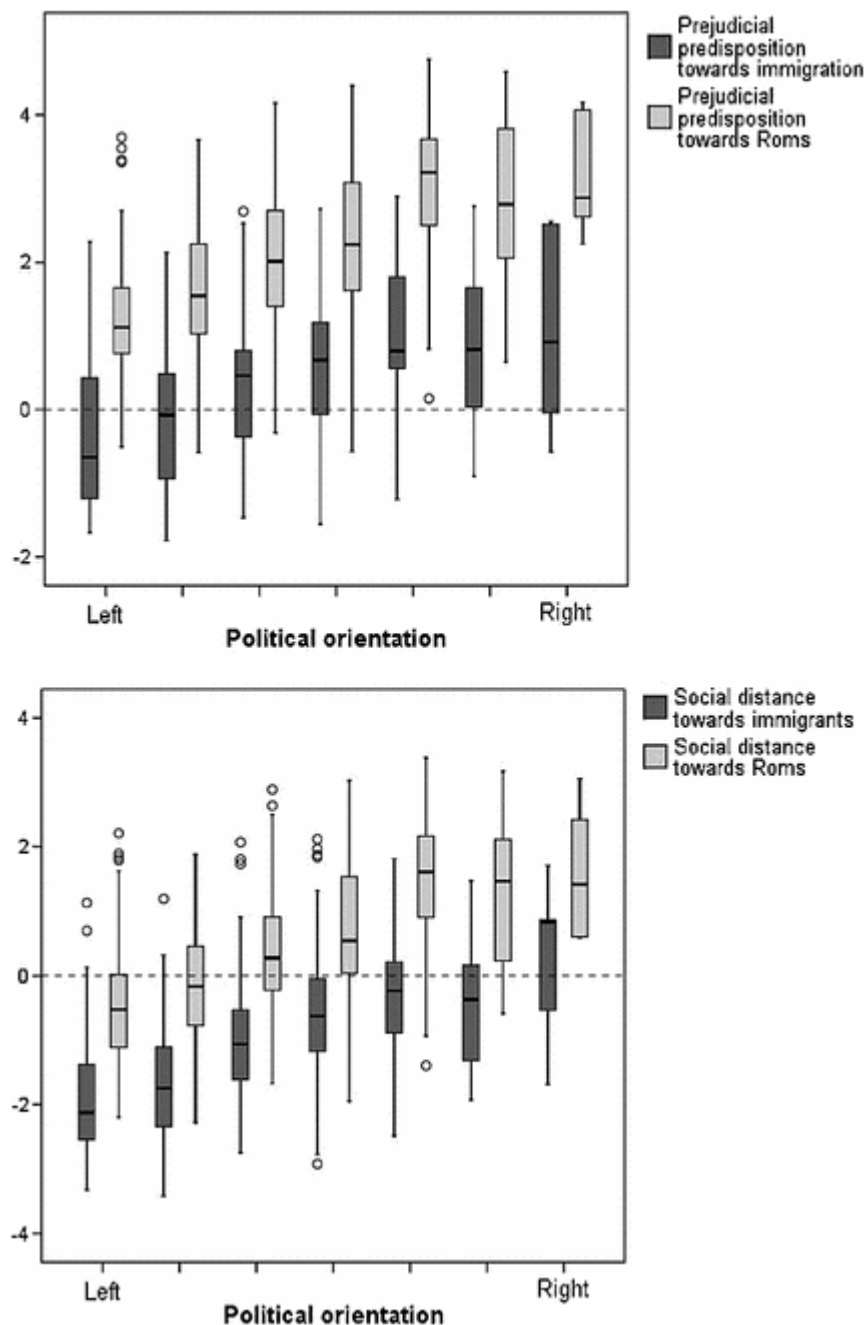
Prejudicial predisposition and Social distance scores with respect to political orientation

Conclusions

In this paper we have focused on some results of a study aimed at investigating prejudices towards the Roma people and migrants. Results show that prejudices toward Roma are still open and direct and less "politically correct". In particular, the findings of IRT show that prejudices towards the Roma people are deeply rooted and that the political orientation is the variable that mainly influences this attitude. If we move from left to right-wing, the social acceptance of Roma decreases. This finding is consistent with many studies on prejudice, which present a strong correlation between political orientation (right-wing side) and a high level of prejudice (Altemeyer 1998; Whitley 1999; Villano and Zani 2007; Passini and Villano 2013; Pew Research Center 2014). The Romani population continue to be not accepted by a large society because they do not conform to the

rules of our country, and are perceived as element of disorder in our culture and generate fear, as some people reported in the questionnaires. According to our results, the most discriminative pairs of polar adjectives towards the Roma people are "good–bad" and "attractive–unattractive". Regarding social distance, Roma are accepted as friends, but not as neighbors or guests. The relationship between negative vision and level of acceptance is inverse: the growth of a negative view of the Roma people causes the level of acceptance to decrease, regardless of the age or gender of the sample. Not so large, instead, is the social distance for migrants, reflecting the fact that the prejudicial predisposition towards Roma is very negative.

These results confirm a general tendency and peculiarity of prejudice towards Roma: open, direct, racist, full of negative emotions like reject or fear, in other words, delegitimizing (Bar-Tal 1990). All the sample—even respondents with a lower level of prejudice- characterize the Roma people as agitated, passive, unattractive and bad (a sort of "natural" traits) and this finding confirms once again that anti-Roma prejudice is ancestral and may function as a common marker for cultural identity (Pérez et al. 2001). The Roma people represent not only an outgroup, but an outsider in the social map of human identity (ontologisation). As our findings show, Roma are excluded from society especially from those who have a great sense of Italian national identity, and those respondents are more prone to show higher prejudicial predisposition and especially social distance towards both migrants and the Roma people. This exclusion seems to go beyond ideological prejudice, and serves to create social distance between groups and deny similarities between majorities and minorities (Moscovici and Pérez 1997; Capozza and R 2000; Marcu and Chryssochoou 2005; Villano 2013a, b). Of course, the results presented here can only be a starting point for discussing ideas and suggestions. Other studies can be done, but the reality is the fact that the Roma people continue to be the most discriminated even with respect to migrants and to be classified as a separate reality to which we will not ever get used.

Notes

1. 1.

   Following the indication of the Council of Europe, "the term Roma […] refers to Roma, Sinti, Kale and related groups in Europe, including Travellers and the Eastern groups, and covers the wide diversity of the groups concerned, including persons who identify themselves as Gypsies". Council of Europe, *Descriptive Glossary of terms relating to Roma issues*, version dated 18 May 2012.

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Table 1 National identity: posterior estimates of item parameters for the unidimensional graded response model

Item	Discrimination parameters			Thresholds		
	Estimate	SD	CI			
Being Italian is important to me	1.44	0.13	[1.22, 1.72]	-2.19	-0.18	1.48
I identify myself as Italian	1.64	0.17	[1.38, 2.01]	-2.50	-0.27	1.98
I am very proud to be Italian	1.30	0.11	[1.11, 1.52]	-1.84	0.15	1.80
I often regret being an Italian	0.37	0.04	[0.29, 0.45]	-1.34	-0.11	0.89
Being Italian reflects my personality	0.89	0.07	[0.77, 1.02]	-1.44	0.41	1.76

Table 2 'Prejudicial predisposition' and 'Social distance' towards migrants and Roma people: posterior estimates of the item parameters of the graded response model

	Discrimination parameters			Thresholds	
	Estimate	SD	CI		
Migrants					
Prejudicial predisposition					
Good–bad	2.14	0.25	[1.71, 2.70]	0.13	3.12
Positive–negative	2.35	0.31	[1.84, 3.05]	0.08	3.00
Attractive–unattractive	1.36	0.12	[1.13, 1.61]	-0.54	1.62
Valuable–valueless	0.88	0.08	[0.72, 1.04]	0.33	1.88
Social distance					
Guest	0.99	0.10	[0.80, 1.20]	-0.65	0.82
Neighbor	1.65	0.28	[1.20, 2.29]	0.98	2.18
Friend	1.81	0.39	[1.27, 2.61]	0.84	2.71
Fiance	1.33	0.17	[1.02, 1.70]	-1.17	0.53
Roma					
Prejudicial predisposition					
Good–bad	1.81	0.37	[1.18, 2.61]	0.62	3.75
Attractive–unattractive	0.99	0.11	[0.79, 1.21]	0.04	2.31
Active–passive	0.17	0.05	[0.10, 0.27]	-0.17	0.69
Calm–agitated	0.53	0.07	[0.39, 0.67]	-0.50	0.90
Social distance					
Guest	1.73	0.16	[1.44, 2.08]	-0.54	1.07
Neighbor	1.94	0.20	[1.60, 2.37]	0.71	1.88
Friend	1.87	0.19	[1.52, 2.28]	0.99	2.45
Fiance	1.27	0.11	[1.06, 1.50]	-1.16	0.52

Table 3 Correlation coefficients and 95 % credible intervals for the endogenous latent variables

	PPi	SDi	PPr
SDi	0.542 [*0.451;0.629*]		
PPr	0.518 [*0.429;0.606*]	0.593 [*0.469;0.731*]	
SDr	0.480 [*0.401;0.555*]	0.760 [*0.674;0.845*]	0.906 [*0.817;0.990*]

The acronym indicates the construct considered: *PP* prejudicial predisposition, *SD* social distance—the subscript 'r' or 'i' indicates wether the latent variable refers to Roma or migrants

Table 4 Posterior means of estimated regression coefficients

	PPi	SDi	PPr	SDr
Intercept	0.668****	−0.333****	2.446****	1.057****
National identity	0.127****	0.231****	0.181****	0.190****
Age	−0.004	0.002	−0.003	0.008
Male	0.053	−0.322****	0.037	−0.136
North-central Italy	−0.111	−0.069	−0.091	−0.183**
Lower tertiary education and above	−0.182**	−0.307****	0.016	−0.171
Political position: left	−0.594****	−0.817****	−0.582****	−0.670****
Political position: right	0.478****	0.347****	0.549****	0.654****
Satisfied with economic condition	−0.023	0.035	0.031	−0.014
Small Romani community's size	−0.019	−0.176	−0.420****	−0.399****

The (**) and (*) provide information on coefficients significant at 95 % and 90 %, respectively

Appendix

The collected data are stored in the $(N \times J)$ matrix $\mathbf{X}$ and the $(N \times M)$ matrix $\mathbf{Y}$ of observed responses and the $(N \times P)$ matrix $\mathbf{W}$ of observed person covariates.

- (a) Sample $Z_{ik}^{(y)} | \boldsymbol{\alpha}_k^{(y)}, \boldsymbol{\theta}_i, \boldsymbol{\gamma}_k^{(y)}, \mathbf{Y}$ and $Z_{ij}^{(x)} | \boldsymbol{\alpha}_j^{(x)}, \xi_i, \boldsymbol{\gamma}_j^{(x)}, \mathbf{X}$

  The underlying variable scores are drawn from doubly truncated normal distributions implied by the threshold model. Given a unidimensional or multi-unidimensional normal ogive model and considering an observed categorical indicator V_l for a latent variable η, the posterior distribution of the underlying variable score for subject i and item l, Z_{il}, is given by

  $$Z_{il} | \alpha_l, \boldsymbol{\eta}, \boldsymbol{\gamma}_k, \mathbf{V}_l \sim \mathcal{N}(\alpha_l \eta_i, 1) I(\gamma_{l,c-1} < Z_{il} < \gamma_{l,c}) \qquad if \ V_{il} = c$$

  Let's denote with $\mathbf{Z}_x$ and $\mathbf{Z}_y$ the $(N \times J)$ and $(N \times K)$ matrices of the simulated values for the underling variables of the X and Y indicators.

- (b) Sample $\alpha_{k_m}^{(y)} | \mathbf{Z}_y, \{\boldsymbol{\theta}_i\}, \mu_{\alpha_y}, \sigma_{\alpha_y}^2$ and $\alpha_j^{(x)} | \mathbf{Z}_x, \{\xi_i\}, \mu_{\alpha_x}, \sigma_{\alpha_x}^2$

  Given the N-dimensional vector $\boldsymbol{\eta}$ containing the latent variable scores for a given latent variable, the N-dimensional vector $\mathbf{Z}_l$ for the l-th underlying variable can be written as $\mathbf{Z}_l = \alpha_l \boldsymbol{\eta} + \mathbf{u}_l$. Considering the prior $\alpha_l \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2) I(\alpha_l > 0)$, the full conditional is truncated normal

  $$\alpha_l | \mathbf{Z}_l, \boldsymbol{\eta}, \mu_\alpha, \sigma_\alpha^2 \sim \mathcal{N}\left((\boldsymbol{\eta}'\boldsymbol{\eta} + \boldsymbol{\sigma}_\alpha^{-2})^{-1}(\boldsymbol{\eta}'\mathbf{Z}_l + \boldsymbol{\sigma}_\alpha^{-2}\mu_\alpha), (\boldsymbol{\eta}'\boldsymbol{\eta} + \boldsymbol{\sigma}_\alpha^{-2})^{-1}\right) I(\alpha_l > 0)$$

- (c) Sample $\boldsymbol{\gamma}_k^{(y)} | \{\boldsymbol{\theta}_i\}, \{\boldsymbol{\alpha}_k^{(y)}\}$ and $\boldsymbol{\gamma}_j^{(x)} | \{\xi_i\}, \{\boldsymbol{\alpha}_j^{(x)}\}$

  To draw the threshold parameters for a given item, we consider a Metropolis–Hastings step based on Cowles algorithm. Consider a vector of thresholds, $\boldsymbol{\gamma}_l$ for a one-dimensional ordinal variable V_l with C categories. Cowles algorithm begins by simulating candidate parameters $\gamma_{l,c}^*$ for each free element of $\boldsymbol{\gamma}_l$ from normal distributions centered over the current value of each $\gamma_{l,c}$ truncated at the current values of the thresholds below and above the threshold being simulated

  $$\gamma_{l,c}^* \sim \mathcal{N}\left(\gamma_{l,c}, \sigma_{MH}^2\right) I\left(\gamma_{l,c-1}^* < \gamma_{l,c}^* < \gamma_{l,c+1}\right) \quad for \ c = 1, ..., C-1$$

  Once a set of candidates is generated, the next step in the MH algorithm is to compute the ratio R. In this case, given the truncation of the normal proposal densities, the proposals are asymmetric, and hence, the full ratio must be computed. The Metropolis–Hastings acceptance probability is then given by

  $$min\left[\prod_{i=1}^N \frac{Pr\left(V_{il} = c \middle| \eta_i, \alpha_l, \boldsymbol{\gamma}_l^*\right) f\left(\boldsymbol{\gamma}_l \middle| \boldsymbol{\gamma}_l^*, \sigma_{MH}^2\right)}{Pr\left(V_{il} = c \middle| \eta_i, \alpha_l, \boldsymbol{\gamma}_l\right) f\left(\boldsymbol{\gamma}_l^* \middle| \boldsymbol{\gamma}_l, \sigma_{MH}^2\right)}, 1\right]$$

  The tuning parameter σ_{MH}^2 has been set to obtain an acceptance rate of about 40 %.

- (d) Sample $\boldsymbol{\theta}_i \,|\, \boldsymbol{Z}_y, \{\boldsymbol{\alpha}_k^{(y)}\}, \boldsymbol{B}, \boldsymbol{\Sigma}_\theta, \mathbf{D}$

  Given the structured $(K \times M)$ matrix of discrimination parameters $\mathbf{A}_y$, the K-dimensional vector $\boldsymbol{Z}_i^{(y)}$ can be written as $\boldsymbol{Z}_i^{(y)} = \mathbf{A}_y \boldsymbol{\theta}_i + \boldsymbol{u}_i^{(y)}$. Considering the prior $\boldsymbol{\theta}_i \sim \mathcal{N}_M(\mathbf{B}\boldsymbol{d}_i, \boldsymbol{\Sigma}_\theta)$, the full conditional is normal

  $$\boldsymbol{\theta}_i \,|\, \boldsymbol{Z}_y, \{\boldsymbol{\alpha}_k^{(y)}\}, \boldsymbol{B}, \boldsymbol{\Sigma}_\theta, \mathbf{D}$$
  $$\sim \mathcal{N}_M\big((\mathbf{A}_y' \mathbf{A}_y + \boldsymbol{\Sigma}_\theta^{-1})^{-1}(\mathbf{A}_y' \boldsymbol{Z}_i + \boldsymbol{\Sigma}_\theta^{-1}\boldsymbol{\mu}_i), (\mathbf{A}_y' \mathbf{A}_y + \boldsymbol{\Sigma}_\theta^{-1})^{-1}\big)$$

  where $\boldsymbol{\mu_i} = \mathbf{B}\boldsymbol{d}_i$.

- (e) Sample $\xi_i \,|\, \boldsymbol{Z}_x, \{\alpha_j^{(x)}\}, \mu_\xi, \sigma_\xi^2$

  Given the discrimination parameter vector $\boldsymbol{\alpha}_x$, the J-dimensional vector Z $Z_i^{(x)}$ can be written as $\boldsymbol{Z}_i^{(x)} = \boldsymbol{\alpha}_x \xi_i + \boldsymbol{u}_i^{(x)}$. Considering the prior $\xi_i \sim \mathcal{N}(\mu_\xi, \sigma_\xi^2)$, the full conditional is normal

  $$\xi_i \,|\, \boldsymbol{Z}^{(x)}, \{\alpha_j^{(x)}\}, \mu_\xi, \sigma_\xi^2$$
  $$\sim \mathcal{N}\big((\boldsymbol{\alpha}_x' \boldsymbol{\alpha}_x + \sigma_\xi^{-2})^{-1}(\boldsymbol{\alpha}_x' \boldsymbol{Z}_i^{(x)} + \sigma_\xi^{-2}\mu_\xi), (\boldsymbol{\alpha}_x' \boldsymbol{\alpha}_x + \sigma_\xi^{-2})^{-1}\big)$$

- (f) Sample $\boldsymbol{B} \,|\, \{\boldsymbol{\theta}_i\}, \boldsymbol{\Sigma}_\theta, \mathbf{D}$

  Given the prior distribution for the M-dimensional vector $\boldsymbol{\theta}_i$, $\mathcal{N}_M(\mathbf{B}\boldsymbol{d}_i, \boldsymbol{\Sigma}_\theta)$, and considering the $(N \times M)$ matrix $\boldsymbol{\theta} = [\boldsymbol{\theta}_1 \cdots \boldsymbol{\theta}_N]'$, the multivariate regression model $\boldsymbol{\theta} = \boldsymbol{D}\boldsymbol{B}' + \boldsymbol{E}$, can be written as $vec(\boldsymbol{\theta}) = (\boldsymbol{I}_M \otimes \boldsymbol{D})vec(\boldsymbol{B}') + vec(\boldsymbol{E}) = \widetilde{\boldsymbol{D}}vec(\boldsymbol{B}') + vec(\boldsymbol{E})$, where $vec(\boldsymbol{E}) \sim \mathcal{N}_{NM}(\boldsymbol{0}, \widetilde{\boldsymbol{\Sigma}}_\theta = \boldsymbol{\Sigma}_\theta \otimes \boldsymbol{I}_N)$ Considering the prior $vec(\boldsymbol{B}') \sim \mathcal{N}_{MP}(vec(\boldsymbol{\mu}_{B_0}'), \sigma_{B_0}^2 \boldsymbol{I}_{MP})$, the full conditional is normal

  $$vec(\boldsymbol{B}') \,|\, \{\boldsymbol{\theta}_i\}, \boldsymbol{\Sigma}_\theta, \mathbf{D} \sim \mathcal{N}_{MP}\big(vec(\boldsymbol{\mu}_B), \boldsymbol{\Sigma}_B\big)$$

  where

  $$vec(\boldsymbol{\mu}_B) = \big(\widetilde{\boldsymbol{D}}' \widetilde{\boldsymbol{\Sigma}}_\theta^{-1} \widetilde{\boldsymbol{D}} + \sigma_{B_0}^{-2} \boldsymbol{I}_{MP}\big)^{-1}$$
  $$\boldsymbol{\Sigma}_B = \big(\widetilde{\boldsymbol{D}}' \widetilde{\boldsymbol{\Sigma}}_\theta^{-1} \widetilde{\boldsymbol{D}} + \sigma_B^{-2} \boldsymbol{I}_{MP}\big)^{-1}$$

- (g) Sample $\boldsymbol{\Sigma}_\theta \,|\, \{\boldsymbol{\theta}_i\}, \boldsymbol{B}, \boldsymbol{D}$

  The prior is $\boldsymbol{\Sigma}_\theta^{-1} \sim Wish(N_0, \boldsymbol{S}_0)$ con $N_0 = 3$ and $\boldsymbol{S}_0 = 0.1\boldsymbol{I}$. Therefore, the posterior is $\boldsymbol{\Sigma}_\theta \sim Inv - Wish(N_0 + N, \boldsymbol{S}_0 + (\boldsymbol{\theta} - \boldsymbol{D}\boldsymbol{B}')(\boldsymbol{\theta} - \boldsymbol{D}\boldsymbol{B}')')$.

- (h) Sample $\mu_\xi \,|\, \{\boldsymbol{\xi}_i\}, \sigma_\xi^2$

  The prior distribution for μ_ξ in normal $\mathcal{N}(\mu_{\xi_0}, \sigma_{\xi_0}^2)$, the full conditional is normal

  $$\mu_\xi \,|\, \{\boldsymbol{\xi}_i\}, \sigma_\xi^2 \sim \mathcal{N}\big[(N\sigma_\xi^{-2} + \sigma_{\xi_0}^{-2})^{-1}(N\sigma_\xi^{-2}\bar{\xi} + \sigma_{\xi_0}^{-2}\mu_{\xi_0}), (N\sigma_\xi^{-2} + \sigma_{\xi_0}^{-2})^{-1}\big]$$

here $\bar{\xi}$ is the sample mean $\bar{\xi} = \boldsymbol{\xi}' \mathbf{1}_N / N$, where $\mathbf{1}_N$ is a N-dimensional vector of ones.

- (i) Sample $\sigma_\xi^2 \mid \xi_i$

  The prior is $\sigma_\xi^{-2} \sim Ga(n_{\xi_0}, s_{\xi_0})$ con $n_{\xi_0} = s_{\xi_0} = 0.001$. Therefore, the posterior is $\sigma_\xi^{-2} \sim Ga\left(n_{\xi_0} + \frac{n}{2}, s_{\xi_0} + \frac{1}{2}\sum_{i=1}^n (\xi_i - \bar{\xi})^2\right)$