Measuring and detecting situations of need and deprivation using Graded Response Models

Corsini, Lorenzo and Martelli, Irene

June 2017

Measuring and detecting situations of need and deprivation using Graded Response Models

Lorenzo Corsini[1], University of Pisa

Irene Martelli[2], St. Anna School of Advanced Studies

ABSTRACT

In the present work we exploit information on living conditions of individuals to build an estimation of their degree of need and deprivation. The information we use have often subjective components that help in identifying situations of need and we assume that deprivation is a latent variable that we estimate with IRT models on Italian data. We then relate this estimated trait to more objective and observable variables that thus could be used within policy actions and welfare programs to pinpoint situations where the estimated deprivation is high.

JEL CODES: I32; I38; C40.

Keywords: Item Response Theory; IRT; deprivation; degree of need; welfare programs.

1. Introduction

The measurement of poverty and the detection of situations of need and deprivation has always been a major concern for social scientists and policy makers: in our contribution we start from the concept of deprivation, something that describes a state of disadvantage relative to rest of the community (see Townsend 1987) and we propose a recent statistical method to identify and measure situations of deprivation (which we also call situations of need). In this sense we are not only referring to observable lack of monetary resources but we want to consider also relative aspects, accessibility to goods and services and subjective and psychological perceptions.

In particular, we use Item Response Theory (IRT) to estimate a variable that captures the degree of deprivation and need of a household. This methodology exploits qualitative information ("items") to estimate a latent variable ("trait") that is related to the observed items: here we use qualitative data on living conditions to estimate the latent trait representing degree of deprivation. Previous analyses of deprivation that use IRT methodology are Cappellari and Jenkins (2007) and Szeles and Fusco (2013): the latter uses an IRT model for binary items to estimate deprivation in Luxemburg.

[1] lcorsini@ec.unipi.it
[2] i.martelli@santannapisa.it

In our analysis we use Italian data on living conditions from the EU-SILC survey: in doing this we extend the IRT model to allow for the use of both binary and non-binary variables and we thus rely on Graded Response models.

The estimation of the latent trait representing deprivation is particularly relevant from a policy point of view. First, welfare policies are conceived to help individuals that are actually in need and thus, a method that highlights these situations without relying only on income and money is particularly useful. Second, welfare policies have to take into account their impact on the economic behaviour and incentives of the recipients and this impact actually depends on the initial degree of need of recipient. This latter issue is particularly relevant in labour policies and unemployment insurance systems: in fact, the degree of need affects the job search process and interact with the presence of unemployment benefits (see Bloemen and Stancanelli 2001, Chetty 2008 and Corsini 2013).

Moreover, to further provide useful policy indications, we try to relate the estimated degree of need to other variables that could be easily observed by a policy maker (income, wealth, household composition). In fact, it would be useful to find variables that are easy to observe and that offer strong indications of situations of need (i.e. that are strongly correlated with the estimated degree of need). In practice, we use information that are hard to observe for administrative offices to assess the actual degree of need and we then relate it to easily observable variables.

2. Statistical method

Our aim is to assess the directly unobservable *degree of need and deprivation of households* through an Item Response Theory (IRT) model that allows the simultaneous estimation of both the households' score on a need and deprivation scale and the items' properties (van der Linden and Hambleton, 2013).

All IRT methods rely on three principal assumptions: (i) Item responses are affected only by the latent trait; (ii) a change in the probability of a response is fully described by the item characteristic curve (ICC) and the boundary characteristic curve (BCC) for binary and graded items, respectively, that is, ICCs and BCCs show how the probability of a response changes given a change in the latent trait; (iii) pairwise item responses are statistically independent given the underlying latent trait.

Given the data available for our study and our purposes, we focus on the Samejima's Graded Response Model (GRM) (Samejima, 1996) that allows us to analyze data in their original form, without any loss of information due to data transformation. The GRM is specified as follows:

[Households] Let consider a random vector, $\boldsymbol{Y}_i$, of p item responses for the i-th household ($i = 1, \dots n$) and the resultant observed responses, $\boldsymbol{y}_i = (y_{i1}, \dots, y_{ip})$. Let denote with θ_i the latent trait of the i-th household. Latent trait is assumed to follow a standard normal distribution.

[Items] Let consider a set of p ordinal items, Y_j, where each item has K_j ordered categories, indexed by k. Hence, each item is described by $K_j - 1$ thresholds or boundaries: $\kappa_{j,1}, \dots, \kappa_{j,K_j-1}$. The probability to reach category k or higher increases monotonically as the latent trait grows and the boundaries satisfy the order constraint: $\kappa_{j,1} < \cdots < \kappa_{j,K_j-1}$.

The GRM is specified with respect to the probability that the response will be observed in *category k or higher*: the probability π_{ijk} that the i-th respondent will achieve the k-th category on item j is hence computed as the probabilities of responding above the lower boundary for the category ($\pi^*_{ij,k}$) minus the probability of answering above the category's upper boundary ($\pi^*_{ij,k+1}$):

$$\pi_{ij,k} = P\left(Y_{ij} = k \middle| \theta_i\right) = \pi^*_{ij,k} - \pi^*_{ij,k+1} \qquad\qquad \theta_i \sim N(0,1)$$

where $\pi^*_{ij,1} = 1$, $\pi^*_{ij,K_j+1} = 0$ and $\pi^*_{ij,k} = P\left(Y_{ij} \geq k \middle| \theta_i\right) = \frac{\exp\left(\alpha_j\theta_i - \kappa_{j,k}\right)}{1 + \exp\left(\alpha_j\theta_i - \kappa_{j,k}\right)}$.

The discrimination parameter α_j represents the slope of the response functions and does not vary between the category responses of the same item: this guarantees the presence of non-negative probabilities. The boundary parameters $\kappa_{j,k}$ vary within an item, according to the order constraint $\kappa_{j,k-1} < \kappa_{j,k} < \kappa_{j,k+1}$, and at each level of $\theta = \kappa_{j,k}$ the household has a probability of 0.5 of endorsing the category.

3. Empirical analysis

We now apply the IRT methodology to estimate the latent construct measuring the degree of need and deprivation using a sample of 1598 Italian households from the 2013 EU-SILC survey. The data give information on living conditions of households (see Table 1): all variables were recoded so that higher values are associated to worse conditions.

Item	Item possible responses (category codes)
Do not have capacity to afford paying for one week annual holiday	No (0); Yes (1)
Do not have capacity to have meat/fish every other day	No (0); Yes (1)
Do not have capacity to face unexpected financial expenses	No (0); Yes (1)
Cannot afford a color TV	No (0); Yes (1)
Cannot afford computer	No (0); Yes (1)
Cannot afford car	No (0); Yes (1)
Not able to keep home adequately warm	No (0); Yes (1)
Has been on arrears on utility bills	No (0); Once (1); More than once (2)
Has been on arrears on mortgage or rent payments	No (0); Once (1); More than once (2)
Burden of housing costs	From Not burden (0) to Heavy burden (2)
Burden of debts from hire purchases or loans	From Not burden (0) to Heavy burden (2)
Ability to make ends meet	From Very easily (0) to With great difficulty (5)

Table 1: Items Description

All items have some subjective components: even data about ownership of goods contain such subjectiveness, in fact individuals signal whether they were able "to afford" buying the specific good. This is an example of the difference between observable variables (easily obtainable by administrative offices) and non-directly observable variables (that only surveys can provide).

Within our estimation, discrimination parameters reflect the capability of the items to discriminate between people with different levels of deprivation, whereas the difficulty and boundary parameters can be viewed as "challenging levels" of the corresponding item. For a given item, high values of the challenging parameters imply lower probabilities to observe responses in positive categories.

We use all available items that satisfy the threes fundamental IRT assumptions mentioned above. Following the item selection and testing approach described in Szeles and Fusco (2013), we apply the Mokken Scale Procedure (MSP) where the appropriateness of the scale is measured by Loevinger's H coefficient (see Hardouin et al., 2011). The Cronbach's alpha is also computed to assess internal consistency between items.

We implemented MSP and identified "Burden of debts from hire purchases or loans" as a poor indicator of deprivation and we thus excluded it from the analysis. This result may be due to the fact that those having burden from debts were able to obtain a loan, so that their financial condition was not particularly problematic. Our final set of items has good scale properties (Loevinger's H coefficient is 0.62) and internal consistency (Cronbach's alpha is 0.75).

Our final set of items was used to estimate the latent trait score: the results of the GRM are contained in Table 2 and show that “Incapacity to afford one week annual holiday”, “Incapacity to face unexpected financial expenses” and “Ability to make ends meet” have high-specific discrimination parameters, representing the most informative items on deprivation. Moreover, “Ability to make ends meet” and “Burden of housing costs” are associated with higher probabilities of responses in higher categories (i.e. the estimation for their challenging levels are lower than for the remaining items). This means that families having an average perception of deprivation believe that those two aspects represent the main consequence of deprivation.

	Discrimination parameters			Difficulty parameters														
	$\hat{\alpha}_j$	SE	P>|z|	$\hat{\kappa}_1$	SE($\hat{\kappa}_1$)	P>|z|	$\hat{\kappa}_2$	SE($\hat{\kappa}_2$)	P>|z|	$\hat{\kappa}_3$	SE($\hat{\kappa}_3$)	P>|z|	$\hat{\kappa}_4$	SE($\hat{\kappa}_4$)	P>|z|	$\hat{\kappa}_5$	SE($\hat{\kappa}_5$)	P>|z|
Do not have capacity to afford paying for one week annual holiday	3.074	0.106	0.000	-0.020	0.016	0.206												
Do not have capacity to have meat/fish every other day	2.088	0.080	0.000	1.391	0.035	0.000												
Do not have capacity to face unexpected financial expenses	3.285	0.115	0.000	0.280	0.016	0.000												
Cannot afford a colour TV	1.440	0.274	0.000	4.814	0.717	0.000												
Cannot afford computer	1.948	0.144	0.000	2.734	0.121	0.000												
Cannot afford car	1.690	0.129	0.000	2.891	0.142	0.000												
Ability to keep home adequately warm	2.296	0.082	0.000	1.112	0.028	0.000												
Has been on arrears on utility bills	1.805	0.078	0.000	1.826	0.050	0.000	1.953	0.055	0.000									
Ability to make ends meet	2.926	0.078	0.000	-3.031	0.072	0.000	-1.963	0.032	0.000	-0.873	0.019	0.000	0.315	0.017	0.000	1.110	0.017	0.000
Burden of housing costs	1.637	0.052	0.000	-3.328	0.075	0.000	-0.314	0.020	0.000									
Arrears on mortgage or rent payments	1.876	0.103	0.000	2.424	0.083	0.000	2.628	0.093	0.000									

Table 2: Items parameters estimates for the GRM

4. Detecting situations of need and policy implications

We want now to assess how the estimated score variable (the degree of need) is correlated to some easily observable variables and, therefore, we want to assess to which extent it is possible to identify situation of need (i.e. high values of the score variable) using easy observable variables. In this process we are not interested in any causal relationship, we simply want to highlight which variables should be looked at if we want to identify situations of need. This is important for welfare and redistributive policies because it gives direct information on which households should be aided. We will focus on the following variables: household gross income (total, per member and per equivalised member), poverty risk (income lower than 40% of median), taxes on wealth (which is a proxy for wealth), ownership of dwelling, household size and equivalised size.

The correlation coefficients between each of the above variables and our estimation of the deprivation score is reported in Table 3: variables with high correlation performs well in detecting which households to aid.

Variable	Correlation Coefficient
Total Gross Income	-0.4014
Gross Income per household member	-0.4047
Gross Income per equivalised household member	-0.4347
At poverty risk	0.3686
Taxes on wealth	-0.2227
Own dwelling	0.2200
Household size	0.0596
Household equivalised size	0.0497

Table 3: Correlation between observable variables and the degree of need and deprivation

As expected, households with lower income/resources are associated to higher degree of deprivation: however, the correlation is far from being large. Of all the possible observable variables, total gross income per equivalised member appears to be the best option to detect deprivation. On the contrary, household size has little correlation and should thus not be used directly to determine who should receive aid.

As an alternative policy analysis, we assess what would be the degree of penetration of policies that aid households identified by certain poverty thresholds. A common convention for this is to identify poverty at 60% of the median of variables measuring resources. Basically, we identify households to aid using thresholds computed from observable variables and we then check to what extent aiding them provide help to households truly in need according to our estimation of deprivation (i.e. identified by a threshold derived from our deprivation score). Results are reported in Table 4.

Observable variable used to identify threshold	Share of households receiving aid	Share of individual in need receiving aid	Share of individual not in need receiving aid
Total Gross Income	22.11%	52.45%	18.59%
Gross Income per equivalised household member	20.10%	54.85%	16.07%
Gross Income per household member	21.04%	56.04%	16.98%
Taxes on wealth (as a proxy of wealth)	43.15%	71.94%	39.81%
Taxes on wealth per household member	43.04%	72.32%	39.65%
Taxes on wealth per equivalised household member	44.70%	73.17%	41.40%
All variables at the same time	8.64%	32.77%	5.84%

Table 4: Households receiving aids and thresholds

Our results signal relevant policy issues: policies that offers aid to households directly on the base of observable income and wealth are often ineffective (do not help a large share of households in need) and produce misspending (offer aid to households not in need). In general, income thresholds produce less effective performances but lower misspending whereas wealth thresholds are more effective but also induce more misspending. Interestingly, using a stringent policy where all thresholds must be met to receive aid produces a partial effectiveness but almost abate misspending.

5. Conclusions

We proposed a statistical procedure to measure a latent variable representing deprivation and analysed how it is correlated to observable variables. We applied this technique to Italian data but similar analyses could be developed for other countries. As for Italy, we found that the best indication for deprivation comes from income per equivalised member. We also have a clean cut indication that redistributive policies based directly on households size should be avoided. Finally, we found that delivering aid using thresholds based on income and wealth presents severe shortcoming as it often neglects households in need and can help those not in need.

REFERENCES

Bloemen, H. G. and Stancanelli, E. G. F (2001), “Individual Wealth, Reservation Wages, and Transitions into Employment”, *Journal of Labor Economics*, 19 (2), 400-439.

Cappellari, L., Jenkins, S.P. (2007), “Summarizing Multiple Deprivation Indicators”. In: Jenkins, S.P, Micklewright, J. (eds.) *Inequality and Poverty Re-examined*, 166–184. Oxford University Press, Oxford.

Chetty R. (2008), “Moral Hazard vs. Liquidity and Optimal Unemployment Insurance”, *Journal of Political Economy*, 116 (2), 173-234.

Corsini (2013), How unemployment benefits affect individuals of different wealth classes: some evidence from Italy, *International Journal of Manpower*, 34 (6), 693 – 711.

Hardouin, J.B., Bonnaud-Antignac, A., Sebille, V., (2011), “Nonparametric item response theory using Stata” *The Stata Journal* , 11 (1), 30–51.

Samejima, F., (1996), "Evaluation of mathematical models for ordered polychotomous responses." *Behaviormetrika*, 23 (1), 17-35.

Szeles, M., and A. Fusco, (2013), "Item response theory and the measurement of deprivation: evidence from Luxembourg data" *Quality & Quantity: International Journal of Methodology*, 47(3), 1545-1560.

Townsend, P., (1987), Deprivation, *Journal of Social Policy*, 16 (2), 125–146.

van der Linden, W. J., and R. K. Hambleton, (2013), *Handbook of modern item response theory.* Springer Science & Business Media.