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STATISTICAL EVIDENCE OF THE SUBJECTIVE WORK QUALITY: THE FAIRNESS DRIVERS OF THE JOB SATISFACTION

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Abstract: *Workers' well-being appears to be strongly influenced by fairness concerns. A key question is how such a relationship could be dissected in order to get a picture where different dimensions of Job Satisfaction (Intrinsic, Extrinsic and Overall) are connected to each of the main fairness facets. Using a large dataset of about 4,100 workers belonging to more than 300 Italian social cooperatives, we aim at giving a statistical answer to this question. First, using the Rasch Rating Scale Model we construct measures of Intrinsic and Extrinsic Job Satisfaction (JS) and measures of Work Intensity in order to divide the workers in three homogeneous clusters: we suppose that a different level of Work Intensity in the organization influences the fairness perception of each worker and therefore his/her subjective quality of work. Second, using a Variable Importance Indicator derived from the Random Forests algorithm, for each group of workers we select the most important fairness drivers in terms of their impact on the different dimensions of the JS. Our main findings are that non-monetary components of fairness play a key role on the JS measure and the importance attributed to different fairness items varies depending on the Work Intensity level, then producing a non-trivial dependence of the JS measures from the fairness drivers.*

Keywords: *Work intensity, rotated nonlinear principal component analysis, rasch analysis, rating scale model, random forests, variable importance.*

1. Introduction

In the social and economic research, the quality of work and its measurement appear as the major target although the concept is, in some sense, elusive ([18], [47]). This is due to its multidimensional nature, where various subjective perceptions on some key features as fairness

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or organizational justice and Job Satisfaction (JS) can lead to composite statistical indicators, which are useful to assess a comprehensive measure of the quality of work. The measurement of the quality of work requires specific questionnaires through which workers provide subjective answers on Likert-type scales, which are translated into quantitative indicators that summarize subjective perceptions ([41]) on each feature of the concept investigated.

Each feature or dimension can then be explained by some "drivers" (explanatory factors) for which we have to: (*i*) identify the possible candidates, (*ii*) verify whether they are coherent with the specific dimension we are inspecting, (*iii*) evaluate how important they are in explaining that dimension.

The fairness of an organization is of central importance to inspect the quality of work since many studies have pointed out its positive impact on JS ([29], [33], [46], [37], [45], [16]). The study of the relationship between fairness and JS with appropriate statistical models is then a challenging issue which needs to be explored in each of the main facets, considering the multidimensional nature of these two constructs. The aim of our paper is to identify which items of the fairness have major impact on JS, taking into account the *WORK INTENSITY*. In fact, we suppose that different levels of *WORK AUTONOMY* and *WORK COMPLEXITY* as well as *WORK RELATIONS* within the organization influence the fairness perception of each worker and, consequently, the quality of work.

In more depth, using data from the Survey on the Italian Social Cooperatives, known as ICSI^{2007} ([11]), carried out in 2007 on 4,134 workers employed in 320 social cooperatives, we inspect the quality of work of such organizations by dissecting their main dimensions and identifying the most important drivers.

To do this we introduce a two-step procedure. In the first step, we use the Nonlinear Principal Component Analysis and the Rasch Rating Scale Model in order to construct two measures of JS (*INTRINSIC* and *EXTRINSIC*) and three measures of *WORK INTENSITY*, which are next used to classify the workers within three clusters differing on their *WORK INTENSITY* level. In the second step, for each *WORK INTENSITY* group we run the Random Forests algorithm using alternatively *INTRINSIC*, *EXTRINSIC*, and *OVERALL* JS as dependent variables and the items of the fairness as predictors. From each Random Forest we extract a Variable Importance Indicator to select the most important items of the fairness in terms of their impact on the different dimensions of JS, namely the *INTRINSIC*, *EXTRINSIC*, and *OVERALL* JS.

The paper is organized as follows. In Section 2 we introduce the methodology. Section 3 describes the dataset and discusses the empirical results. Section 4 concludes.

2. Methodology

In this section we shortly describe the methodology used in this study to assess the importance of each fairness driver relative to the JS measures computed for different levels of *WORK INTENSITY*.

2.1 Step one: constructing the quality of work measures

Measures of psychological constructs for quality of work assessment as motivation, fairness and satisfaction are multidimensional by nature. From a statistical point of view, these are "latent variables" and they are inferred from other observable indicators, such as questionnaire items designed to elicit responses related to an attitude or preference.

To obtain measures for the quality of work we proceed as follows.

Nonlinear Principal Component Analysis

We preliminarily quantify the ordinal categories of each item for each Likert-type scale using the Nonlinear Principal Component Analysis (NPCA) ([20], [36], [35], [34]). The optimal quantifications assigned to the categories of each of the r items are obtained by minimizing the following loss function over $\mathbf{O}$, $\mathbf{q}_j$'s and $\mathbf{b}_j$'s, $j = 1,\dots,r_j$, simultaneously:

$$\sigma^2\left(\mathbf{O}; \mathbf{q}_1,\dots,\mathbf{q}_r; \mathbf{b}_1,\dots,\mathbf{b}_r\right) = \frac{1}{r}\sum_{j=1}^{r} tr\left\|\mathbf{O} - \mathbf{q}_j \mathbf{b}'_j\right\|^2$$

with $tr\|\cdot\|^2$ the trace operator of the squared norm of a matrix, $\mathbf{O}$ the $n\times p$ matrix of object scores for the n subjects (where p is the number of components), $\mathbf{q}_j$ the $n\times 1$ vector containing the category quantifications of item j for the n subjects, and $\mathbf{b}_j$ the $p\times 1$ vector containing the loadings of item j on the p components. In order to make the interpretation of loadings easier, we rotated the NPCA solution using the Varimax method with the Kaiser normalization ([19]).

To evaluate the obtained rotated NPCA solution, we used the following goodness-of-fit statistics: the Generalized Cronbach's Alpha × 100 (GCA) and the percentage of the Variance-Accounted-For (VAF) of the rotated solution. These two normalized statistics increase from 0 to 100 with the goodness of fit of the obtained solution.

Rasch Analysis with the Rating Scale Model

Starting from the NPCA results, in this step we obtain the measures of quality of work for each subdimension of the construct using the Rasch Analysis with the Rating Scale Model (RSM) ([1], [8], [9], [12], [15]). According to this model, the probability that worker i could give a specific answer a to the item j with $(c + 1)$ ordered response categories is obtained as:

$$\pi_{ija} = P(A_{ij} = a) = \frac{\exp\sum_{h=0}^{a}[\gamma_i - (\delta_j + \tau_h)]}{\sum_{k=0}^{c}\exp\sum_{h=0}^{k}[\gamma_i - (\delta_j + \tau_h)]} \qquad a = 0, 1, \dots, c$$

where $\tau_0 \equiv 0$, so that $\exp\sum_{h=0}^{0}[\gamma_i - (\delta_j + \tau_h)] = 1$.

The probability π_{ija} depends on the worker attitude and item difficulty. The parameter γ_i identifies the level of attitude of worker i, δ_j the mean difficulty to endorse item j and τ_h (the threshold) is the point of equal probability of categories $(h - 1)$ and h. As goodness-of-fit statistics we consider the Rasch's Alpha (RA) index, the raw Score to Measure correlation (SM) index, and the Explained Variance (EV) index. These three normalized statistics increase from 0 to 100 with the goodness of fit of the obtained estimates. Finally, the interpretation and evaluation of the difficulty estimates for each item are based on two standard statistics used in the Rasch Analysis ([50]): Infit and Ptmea (an acceptable solution should have Infit values between 0.6 and 1.4 and Ptmea values higher than 0.3).

2.2 Step two: constructing the Variable Importance Indicator

Classification and Regression Trees (CART) are nonparametric tools for modelling the relationships between a response variable y and a set of predictors **x**. The algorithm partitions (splits) the covariate space into a set of rectangles containing observations that are as homogenous as possible with respect to the response variable. The partition is based on a criterion which allows to select at each split the best covariate and the cut-off point along it ([7]). The main advantage of the trees is their ability in handling with different types of variables (numerical or categorical), as well as with missing values. On the other hand, one of their major concern is the instability, namely the algorithm is overly responsive to the training data, producing models that can change dramatically with small changes in the data ([17]).

A possible solution to this problem is provided by the ensemble learning techniques ([5], [6], [21], [22]), through which poor predictors (*e.g.* trees), called base learners, are combined in such an extent to obtain robust predictors. The theoretical environment relies to [40], who showed that base learner could always improve its performance by training two additional predictors on filtered versions of the input data. Starting from [40], ensemble learning techniques became of central interest among academics. We recall [5], who introduced the Bagging in which multiple predictors are generated and then combined by simple averaging (regression) or voting (classification).

Denoted as $\hat{f}(\mathbf{x})$ the predictions obtained from each base learner, for the regression case the ensemble predictor can be formalized as:

$$\tilde{f}(\mathbf{x}) = \sum_{m=1}^{M} g_m \hat{f}_m(\mathbf{x})$$

where M is the number of base learners grown before the averaging and $\{g_m\}_1^M$ are the corresponding parameters specifying the linear combination.

Ensemble methods differ on the choice of the base learner, how they are derived from the data and the prescription for obtaining the parameters $\{g_m\}_1^M$ ([23], [24]). Trees are ideal candidates since they can capture complex interaction structures within the datasets, and whether sufficiently deep in structure they show low bias. In addition, trees are notoriously noisy, hence, they benefit greatly from the averaging.

The focus of this paper is on the Random Forests introduced in [6] which are one of the most used ensemble learning together with Bagging ([5]) and Boosting ([21]). Every base learner of the Random Forest is obtained by growing a non-pruned tree on a training set which is a different bootstrap sample drawn from the data. An important feature of Random Forests is about the use of Out-Of-Bag (OOB) predictions, where for each observation $\mathbf{z}_i = (\mathbf{x}_i, y_i)$ the algorithm computes the predictions $\hat{f}(\mathbf{x}_i)$ by averaging only those trees grown using a training set not containing $\mathbf{z}_i$.

For improving the accuracy, the injected randomness has to maximize the differences between the base learners of the Random Forests. For this reason, at each successive split during the tree construction additional randomness is put into the trees. Namely, in each interior node of each tree a subset of predictors is randomly chosen. The Random Forest obtained provides an

accuracy level that is in line with Boosting algorithm, while it is faster. For this reason the algorithm can be viewed as an improved version of the Bagging ([25]).
In sum, Random Forests can handle high dimensional data using a large number of trees in the ensemble, also selecting the variables so as to generate a set of very different trees. Furthermore, the algorithm can estimate the variables' importance giving useful insights to better understand how and why some predictors are selected relative to the response variable.
Within the ensemble learning framework, [6] and [22] proposed two alternative Variable Importance Indicators. The first is the Mean Decrease in Accuracy and the second is the Total Decrease in Node Impurity. In this study we use only the first one since the second indicator is proven to be biased ([43], [44], [38]) due to uninformative splits generated by non-pruned trees ([39]).
To compute the Mean Decrease in Accuracy (MDA), when the *m*-th tree is grown the associated OOB sample is passed down the tree and the error (Mean Square Error for regression, misclassification rate for classification) is recorded. Then, the values for the *v*-th predictor (x_v) are randomly permuted in the same sample, and again the error is computed. The difference between the errors obtained is averaged over all the trees of the Random Forest, and the result is used as a measure of the importance associated to the predictor x_v ([30]). The mimicking of x_v through the randomization permits to identify variables that contribute to the predictions, thereby providing a variable selection method for Random Forests. Formally, let the difference between the errors be denoted as $d_{v,m} = (L_{v,m} - L_m)$, where $L_{v,m}$ is the error of predictor *m* on the OOB sample with the *v*-th variable perturbed, and L_m is simply the error of *m*-th predictor. Consequently, the importance measure of the *v*-th variable is:

$$\text{MDA}_v = \frac{1}{M}\sum_{m=1}^{M}\frac{d_{v,m}}{s_{d_{v,m}}}$$

where *M* denotes the number of trees of the Random Forest, and $s_{d_{v,m}}$ is the standard deviation of $d_{v,m}$. To make the interpretation easier, the measure is often expressed in relative terms based upon its observed maximum.

3. Case Study

The data used in this study come from the Survey on the Italian Social Cooperatives, named ICSI^{2007} ([11], [16]). Missing data were removed using the imputation method proposed by [13]. 320 social cooperatives were sampled from the Census 2003 database[1] and 4,134 paid workers answered to the questionnaire. Starting from several Likert-type scales included in the questionnaire, first we construct the JS and the *WORK INTENSITY* measures and then we investigate the importance of the fairness drivers on *INTRINSIC*, *EXTRINSIC* and *OVERALL* JS for different *WORK INTENSITY* groups of workers.

[1] The Census 2003 counts 5,093 operative social cooperatives with 153,284 paid workers.

3.1 Measuring the JS

The JS is used as a proxy of the quality of work and it is of primary importance also in the context of social services sector ([42], [27], [2], [3], [4]). In addition, it is interesting to evaluate not only the *OVERALL* JS but also the subjective level of satisfaction gained from the working activity regarding *EXTRINSIC* as well as *INTRINSIC* aspects. The *EXTRINSIC* JS takes into account the monetary aspects of work (*e.g.*, pay or career advancement) [28]. Conversely, the *INTRINSIC* JS considers non-monetary aspects of work (*e.g.*, the social usefulness of work or the recognition of one work). In this study we construct the Rasch measures of *EXTRINSIC* and *INTRINSIC* JS using the two multi-item scales available in the ICSI^{2007} questionnaire. In a first step, we use the rotated NPCA of 12 quantified variables (fit statistics: GCA=93 and VAF=49) considering two measurable subdimensions (see the first column of Table 1): *EXTRINSIC* JS[2] (5 items) and *INTRINSIC* JS (7 items). The loadings of the rotated solution show that the two subdimensions are not completely disjoint: we expect positive correlation between the two measures obtained with the following Rasch Analysis, and each single measure for a latent subdimension cannot be interpreted as independent from the other.

A preliminary Rasch Analysis suggests to use a 5-level response scale (ordered categories C1, C2-C3, C4, C5-C6, C7) for all these items. The two obtained measures of *EXTRINSIC* and *INTRINSIC* JS show fairly good reliability (RA index equal to 74 and 87, respectively), high score to measure correlation (SM index equal to 94 and 97, respectively) and high explained variance (EV index equal to 54 and 66, respectively). Furthermore, the items do not misfit (Infit index between 0.88 and 1.12) and show high correlation with the related measures (Ptmea index between 0.67 and 0.77).

Table 1. Summary of the procedure for the 2 measures of the JS.

12 items for 2 subdimensions; GCA = 93; VAF = 49

Questions for the JS: **How satisfied are you with...**

Response scale: 1 = "*Strongly unsatisfied*", 2,…, 4 = "*Neither satisfied nor dissatisfied*",…, 6, 7 = "*Strongly satisfied*"

		Rotated NPCA		Rasch Analysis with RSM		
Measures and Items	***Descriptions***	***Loadings***		***Difficulty***	***Infit***	***Ptmea***
EXTRINSIC JS						
RA = 74; SM = 94; EV = 54						
Ambient	Physical work environment	0.59	0.24	0.10	0.99	0.69
Stability	Job stability	0.59	0.20	0.05	1.12	0.68
Hours	Working hours	0.70	0.19	0.04	0.89	0.71
Flexibility	Flexibility of work hours	0.68	0.23	-0.05	0.95	0.69
Security	Job and social security	0.60	0.24	-0.14	1.03	0.68
INTRINSIC JS						
RA = 87; SM = 97; EV = 66						
Career	Achieved and expected career prospects	0.20	0.63	0.98	1.09	0.72
Involvement	Involvement in the decision making process	0.21	0.72	0.44	0.88	0.76
Development	Professional development	0.24	0.67	0.01	0.95	0.73
Recognition	Recognition of his/her work by the cooperative	0.26	0.76	-0.20	0.90	0.77
Transparency	Transparency of procedures	0.25	0.74	-0.31	0.99	0.75
Realization	Self-realization	0.24	0.63	-0.37	1.11	0.70
Autonomy	Autonomy in decision making	0.26	0.58	-0.55	1.09	0.67

Looking at the Difficulty index for the *EXTRINSIC* JS, we note that *Security* is the most easily satisfied aspect, *Ambient* is the most difficult aspect to satisfy, and *Hours* and *Flexibility* have roughly the same mean level of Difficulty to be satisfied. However, the full range of the difficulties of these items appears to be modest (from -0.14 to 0.10). For the *INTRINSIC* JS,

[2] We do not include the item of the wage satisfaction because we consider it separately.

Autonomy is the easiest aspect to satisfy while *Career* is the most difficult one. For this measure, the range of the item difficulties is wider than before (from -0.55 to 0.98).
Table 2 reports some descriptive statistics for the two JS measures.
We note that the two means are positive (higher than the item mean that is fixed to 0), indicating that workers are on average satisfied. The coefficient of variation shows that the *INTRINSIC* JS denotes greater variability.

Table 2. Descriptive statistics for the 2 measures of the JS.

Measures	*Average*	*Std.Dev.*	*Coefficient of variation*	*Correlations*	
EXTRINSIC JS	1.43	1.67	1.17	1.00	
INTRINSIC JS	0.70	1.73	2.47	0.50	1.00

Hence, workers seem to evaluate their satisfaction differently for specific items of intrinsic aspects; then, they show heterogeneity in their evaluation process of this construct. Taking the nature of the variables into account, the correlation between the two measures is positive and rather high (0.50).

3.2 Measuring the WORK INTENSITY

The *WORK INTENSITY* is a psychological construct that is not yet well developed. Sometimes it is viewed as an effort-related activity similar to the work effort concept discussed in the economics literature, and described as the rate of physical and/or mental input to work tasks performed during the working day ([31], [10]). It is difficult to measure such an effort, since it can only be assessed through self-reports or controlled laboratory experiments. In the literature, the main hypothesis is that individuals with higher levels of *WORK INTENSITY* would be less satisfied with a lower psychological well-being ([45]).
In this study, the *WORK INTENSITY* measure was assessed by the rotated NPCA of 15 items considering three measurable subdimensions (Table A1 in the Appendix): *WORK AUTONOMY* (3 items), *WORK COMPLEXITY* (7 items) and *WORK RELATIONS* (5 items). The rotated NPCA solution shows that some items of the subdimension *WORK RELATIONS* have moderately high factor loadings on the subdimension *WORK COMPLEXITY* and *vice versa*. We will further discuss this point when considering the Rasch Analysis.
For the three different response scales used in the study, the Rasch Analysis suggests to merge together categories C2 and C3 for *WORK AUTONOMY* (RA = 76, SM = 94 and EV = 71) categories C1, C2 and C3 for *WORK COMPLEXITY* (RA = 79, SM = 95 and EV = 75) and categories C1 and C2 for *WORK RELATIONS* (RA = 72, SM = 98 and EV = 75). The item diagnostic statistics Infit (between 0.73 and 1.25) and Ptmea (between 0.56 and 0.82) show good results. Among the items of *WORK AUTONOMY* we note that *Organize* and *Manage* are easier to achieve (*i.e.*, the workers organize and manage their work more easily), while *Solve* is more difficult to achieve (*i.e.*, the workers are not able to solve the problems arisen during their work activity). Among the items of *WORK COMPLEXITY*, *Involvement* is easier to achieve while *Decisions* and *Goals* are more difficult. Finally, among the items of *WORK RELATIONS*, *Colleagues* are easier to achieve, while *Volunteers* is more difficult (many workers have no contact with volunteers).
Table A2 in the Appendix reports some statistics for the three measures of *WORK INTENSITY*. We note that the *WORK COMPLEXITY* and the *WORK RELATIONS* have slightly negative means. This signifies that, on average these employees consider their work not so much complex. On the other hand, the *WORK AUTONOMY* shows a slightly positive mean, then suggesting that the

workers perceived a good level of autonomy in what they do. Anyhow, the high values of the coefficients of variation for *WORK COMPLEXITY* and *WORK RELATIONS* indicate that the corresponding perceptions of the workers are not homogenous. The correlations among these three measures are always positive, with *WORK COMPLEXITY* and *WORK RELATIONS* showing the highest value (0.32).

As previously noted, the rotated NPCA solution shows that some items of the subdimension *WORK RELATIONS* have moderately high factor loadings on the subdimension *WORK COMPLEXITY* and *vice versa*. For this reason, and to reduce the number of dimensions of the *WORK INTENSITY* measures, we extract two Principal Components from the three measures of the *WORK INTENSITY* obtained by the Rasch Analysis. In so doing, we are able to explain the 77% of the variance and the loadings (see Table A3 in the Appendix) show that *WORK RELATIONS* and *WORK COMPLEXITY* are strong on the same statistical subdimension. These results suggest the use of the two principal components to group workers with different levels of the *WORK INTENSITY*. For this purpose, we preliminarily use the first and third quartile of the two principal components to compute nine groups of workers with *low*, *medium* and *high bivariate levels* of the *WORK INTENSITY*. The size of each group is reported in Table A4 of the Appendix. Finally, we consider three groups of workers (highlighted in Table A4 with different shades of grey):

- **LOW *WORK INTENSITY* GROUP**: 1,271 workers scoring low on one component and low or medium on the other component of *WORK INTENSITY*;
- **MEDIUM *WORK INTENSITY* GROUP**: 1,049 workers scoring medium on each of the two components of *WORK INTENSITY*;
- **HIGH *WORK INTENSITY* GROUP**: 1,294 workers scoring high on one component and high or medium on the other component of *WORK INTENSITY*.

Hence, we discard 520 workers because they have too different *WORK INTENSITY* components: 255 workers with high component 1 (*WORK AUTONOMY*) but low component 2 (*WORK COMPLEXITY and WORK RELATIONS*), and 265 workers with high component 2 (*WORK COMPLEXITY and WORK RELATIONS)* but low component 1 (*WORK AUTONOMY*).

Table A5 in the Appendix provides the distributions of the three workers' groups defined by different levels of *WORK INTENSITY* and the various characteristics of interviewees, work and cooperatives. Let us consider the three worker characteristics (*Gender*, *Age* and *Education*). We observe that older workers have a relatively higher percentage of low *WORK INTENSITY* (41.3% for workers aged between 50 and 74 years *versus* 35.2% for the Total) and, as expected, the relation between the level of education and the level of *WORK INTENSITY* is confirmed. Substantial differences among the three groups of workers appear when considering the four work characteristics (*Membership*, *Activity Area*, *Contract type* and *Working time regime*). Members are relatively more numerous within the medium and high *WORK INTENSITY* groups (75.2% and 79.7% respectively, *versus* 71.8% for the low *WORK INTENSITY* group) and have the highest percentage of high *WORK INTENSITY* (37.7% *versus* 29.9% for the non-members). The percentage of employees in the service delivery area is higher in groups with low and medium *WORK INTENSITY* (64.2% and 64% respectively), than in the high *WORK INTENSITY* group (53.1%). The workers employed with a permanent contract are located in groups with medium and high *WORK INTENSITY* (80.6% and 83.5% respectively, *versus* 77.7% for the low *WORK INTENSITY* group) and higher percentage of high *WORK INTENSITY* (37.1% *versus* 30.5% for the employees with self-employment and atypical contracts). The full-time employees are in the group with high *WORK INTENSITY* (63.2% *versus* 50.2% and 54.3% for the low and medium *WORK INTENSITY* groups, respectively) and have the highest percentage of high *WORK INTENSITY* (40.4% *versus* only 27.5% for the employees with forced part-time). Considering the two cooperative characteristics (*Activity type* and *Geographical location*), we note that people employed in type A cooperatives mainly belong to medium and high *WORK INTENSITY* group (82.6% and 81.8% respectively, *versus* 71.4% for the low *WORK INTENSITY* group) and have the lowest percentage of low *WORK INTENSITY* (32.1% *versus* 46.5% for the employees in type B cooperatives).

Finally, to show how the JS moves with respect to the *WORK INTENSITY* we plotted on the *x*-axis the three different level of *WORK INTENSITY* (LOW, MEDIUM and HIGH) and on the *y*-axis the averages of the *EXTRINSIC* and *INTRINSIC* JS, computed for each intensity group. In the first two graphs of Figure 1 we depict such a relationship, while the third graph depicts the relationship between the *WORK INTENSITY* (on *x*-axis) and the *OVERALL* JS[3], expressed as the relative frequency of the *very satisfied*[4] workers (on *y*-axis). The graphs report also the *Inferential Confidence Intervals* ([26]). Note that for higher level of *WORK INTENSITY*, the means of the three different types of JS tend to increase. From an economic point of view, these preliminary results confirm the findings of recent studies on the relation between effort and JS ([2], [3], [4]). In fact, within these social/ethical-oriented organizations, the "typical worker" that works more intensively perceives greater satisfaction, is more involved in the organization, and shares the utility function with the organization itself.

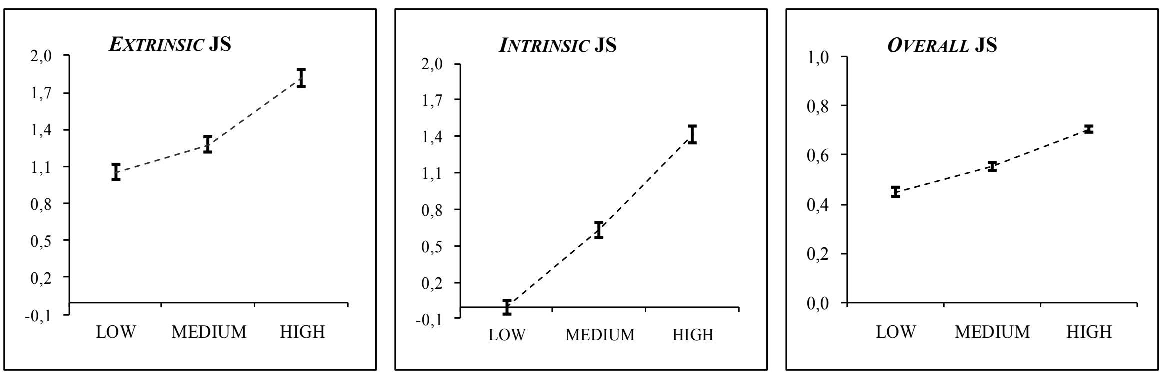

Figure 1. Inferential Confidence Intervals of the means of *EXTRINSIC*, *INTRINSIC* and *OVERALL* JS for each *WORK INTENSITY* group.

However, *within* the three groups of *WORK INTENSITY*, the JS variability is rather high: the correlation ratio is 0.20 for *EXTRINSIC* JS, 0.35 for *INTRINSIC JS* and 0.22 for *OVERALL JS*. In other terms, the workers grouped within the same *WORK INTENSITY* cluster have different JS perceptions. In the next section we check whether this variability can be explained by the workers' perception of fairness.

[3] The *OVERALL JS* is obtained through the question: "*How much are you globally satisfied of your job*?". The response is on ordinal scale from 1 = "*Strongly unsatisfied*" to 7 = "*Strongly satisfied*".

[4] Very satisfied workers scored 6 (*Satisfied*) or 7 (*Strongly satisfied*) on *OVERALL JS*.

3.3 The importance of the fairness drivers on the JS for different levels of WORK INTENSITY

The organizational justice or fairness perception can be detected in relation to many different aspects of work ([37], [45], [32]). For example, in one recent study, [49] considered the effects of *PROCEDURAL JUSTICE*[5] and *DISTRIBUTIVE JUSTICE*[6] on the feeling of inclusion or belongingness to a particular organization. Moreover, the authors studied the effects of *INTERACTIONAL JUSTICE*[7] on the quality of the Leader-Member eXchange relationships (LMX) with their immediate superiors. Their final hypothesis is that organizational identification and LMX have a heavy effect on the job performance, via the moderator effect of the voluntary learning behaviour of employees.

Following the route outlined in the organizational research, we considered the three multi-item scales included in the ICSI^{2007} questionnaire (concerning the *DISTRIBUTIVE*[8], *PROCEDURAL* and *INTERACTIONAL FAIRNESS*) as drivers of the three types of JS. The general questions, the response scales, and the corresponding items are listed below.

- *DISTRIBUTIVE FAIRNESS*: *"Do you think that your overall pay is fair compared with…"*
  1 = "*Much less than fair*", 2,…, 4 = "*Fair*",…, 6, 7 = "*Much more than fair*"
  (*i*) *Training* (*ii*) *Responsibility* (*iii*) *Effort* (*iv*) *Stress* (*v*) *Loyalty*
  (*vi*)*Wage Colleagues* (*vii*) *Wage Others* (*viii*) *Wage Superiors* (*ix*) *Coop Resources*;
- *PROCEDURAL FAIRNESS*: "*How much you agree with the following statements?*"
  1 = "*Strongly disagree*", 2,…, 6, 7 = "*Strongly agree*"
  (*i*) *Guidelines* (*ii*) *Information* (*iii*) *Equality* (*iv*) *Target* (*v*) *Respect*;
- *INTERACTIONAL FAIRNESS*: "*Your supervisor or your superiors…*"
  1 = "*Definitely not*", 2,…, 4 = "*Neither yes nor no*",…, 6, 7 = "*Definitely yes*"
  (*i*) *Availability* (ii) *Personal needs* (*iii*) Working needs (*iv*) Listening
  (*v*) Advices (*vi*) Attention.

The descriptions of the 20 items are listed in the second column of Table 3. Using the statistical approach described in section 2.1, we have then verified the coherence of these items for each dimension of fairness (results are available upon request). These groups of items are then used in the Random Forests as predictors (drivers) for the three types of JS (dependent variables), taken one at a time. Finally, for each Random Forest we computed the variable importance indicator MDA[9] (section 2.2) in correspondence of each item. Figure 2 gives a graphical representation of the implemented models.

Results in Table 3 and Figure 3 lead to conclude that workers with low *WORK INTENSITY* give high importance to *PROCEDURAL* and *INTERACTIONAL FAIRNESS* facets (average MDA from 69.7 to 80.8), while *DISTRIBUTIVE FAIRNESS* shows lower importance for *EXTRINSIC* and *OVERALL* JS (average MDA from 41.9 to 55.9), except in the case of *DISTRIBUTIVE FAIRNESS – OTHERS* on *INTRINSIC* JS (average MDA equal to 76.8). In particular, *Respect* and *Working needs* result key drivers for the three models inspected in the analysis (see Figure 3, graphs on the left): this means that workers belonging to this group are especially interested in being treated with the promised respect from the organization and they desire that superiors are sensitive to their job-

[5] The *PROCEDURAL JUSTICE* is the perceived fairness of the formal allocation processes.
[6] The *DISTRIBUTIVE JUSTICE* is the perceived fairness of one's outcomes with respect to the output/input ratio.
[7] The *INTERACTIONAL JUSTICE* is the perceived fairness concerning the treatments received in the organization.
[8] The *DISTRIBUTIVE FAIRNESS* is distinguished between *INDIVIDUAL* and *OTHERS*.
[9] A similar approach was used by [14], [51] and [48]. We expressed the measure in relative terms based upon its observed maximum.

needs. Furthermore, when using the *INTRINSIC* JS as dependent variable, the first four drivers exhibit almost the same importance.
Instead, workers with medium *WORK INTENSITY* seem to be focused on *PROCEDURAL FAIRNESS* (Table 3). In detail, when *INTRINSIC* JS is used as dependent variable the most important drivers are *Respect* (MDA=100), *Guidelines* (MDA=98.7), *Equality* (MDA=92) and *Targets* (MDA=91.1). On the other hand, when the dependent variable is the *EXTRINSIC* JS, these workers give more importance to the cooperative *Guidelines* (MDA = 100), also showing a large distance with respect to the remaining drivers (see Figure 3, graphs in the middle).

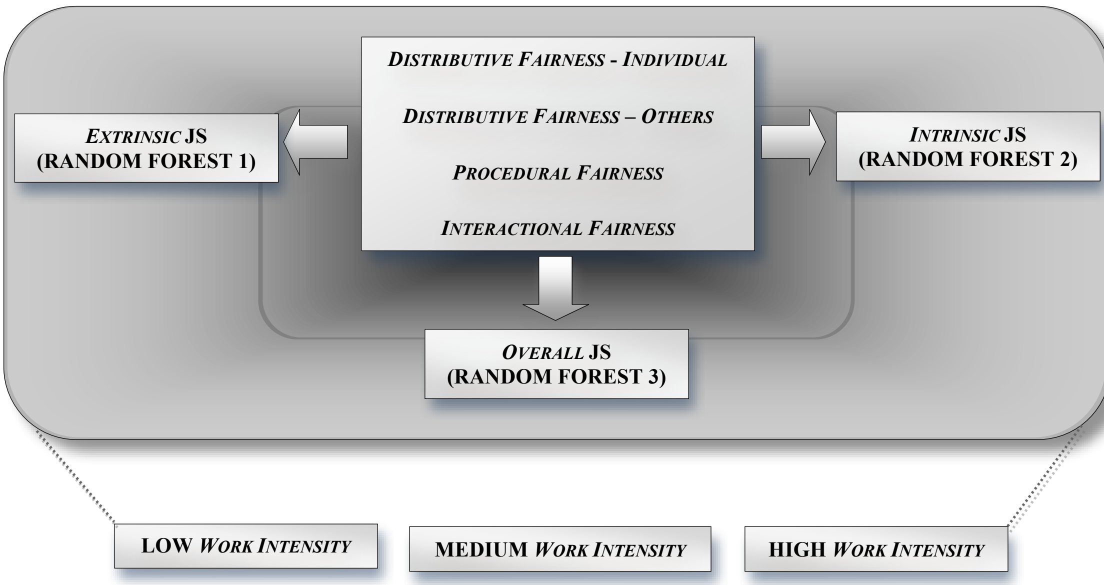

Figure 2. Random Forests run for the 3 JS measures (*INTRINSIC*, *EXTRINSIC*, and *OVERALL*) using the 4 fairness components (*DISTRIBUTIVE FAIRNESS – INDIVIDUAL*, *DISTRIBUTIVE FAIRNESS – OTHERS*, *PROCEDURAL FAIRNESS*, and *INTERACTIONAL FAIRNESS*) and computed for each *WORK INTENSITY* group (LOW, MEDIUM, and HIGH).

Finally, workers with high *WORK INTENSITY* do not give particular importance to a specific dimension of fairness (average MDA from 44.1 to 58.9). Considering the single drivers, workers pay much more attention to the cooperative resources (MDA of *Coop Resources* equal to 100) when the dependent variables are *EXTRINSIC* and *OVERALL* JS. This entails that workers with high *WORK INTENSITY* are more involved in the cooperatives and, consequently, they are interested in their economic resources. In the case of *INTRINSIC* JS, *Stress* is the most important driver (MDA=100), underlying its relevance for the employees that provide a high job effort. In addition, it is interesting to note that the MDA for *Coop Resources* and *Stress* shows a considerable distance from the MDA computed in correspondence of the remaining drivers (see Figure 3, graphs on the right).

Table 3. The MDA Variable Importance Indicator of the fairness drivers on JS for three different levels of *WORK INTENSITY*.

	WORK INTENSITY	RANDOM FOREST 1 *EXTRINSIC JS*			RANDOM FOREST 2 *INTRINSIC JS*			RANDOM FOREST 3 *OVERALL JS*		
	DESCRIPTIONS	**LOW**	**MEDIUM**	**HIGH**	**LOW**	**MEDIUM**	**HIGH**	**LOW**	**MEDIUM**	**HIGH**
DISTRIBUTIVE FAIRNESS - INDIVIDUAL		**44.7**	**66.5**	**53.8**	**55.9**	**60.0**	**61.2**	**41.9**	**60.5**	**48.6**
Training	Training and experience	44.9	81.2	52.7	55.1	65.7	53.9	58.8	54.6	56.7
Responsibility	Responsibility and role	37.3	66.0	61.7	51.6	51.7	53.3	36.4	83.4	45.4
Effort	Effort required	59.6	76.4	55.1	54.8	67.6	45.4	47.4	61.0	48.9
Stress	Stress and tension	53.8	57.9	45.6	63.7	67.5	100.0	35.6	74.4	63.0
Loyalty	Loyalty to the cooperative	28.0	51.2	53.7	54.3	47.4	53.4	31.5	29.1	29.2
DISTRIBUTIVE FAIRNESS - OTHER		**48.0**	**47.9**	**55.9**	**76.8**	**65.1**	**63.8**	**42.7**	**24.6**	**58.9**
Wage Colleagues	The wages of colleagues in the cooperative	46.1	45.7	35.8	50.2	81.4	48.7	37.8	27.1	36.6
Wage Others	The wages of employees in other organizations	60.9	60.5	37.9	91.2	78.6	44.0	28.9	18.8	24.6
Wage Superiors	The wages of superiors	40.5	32.0	49.8	76.9	49.6	83.7	43.0	32.6	74.3
Coop Resources	The economic resources of the cooperative	44.3	53.2	100.0	88.7	50.6	78.9	61.2	20.0	100.0
PROCEDURAL FAIRNESS		**79.4**	**60.9**	**51.1**	**79.7**	**88.5**	**64.0**	**70.9**	**58.9**	**42.0**
Guidelines	Gives advice and guidelines	72.2	100.0	72.1	70.1	98.7	83.7	64.8	97.0	68.7
Information	Collects complete information on worker activity	60.0	60.4	58.7	67.2	60.9	53.7	71.8	33.6	44.9
Equality	Treats its workers in the same manner	92.4	39.6	31.9	64.4	92.0	72.2	80.0	44.6	41.3
Target	Has clear and shared goals	72.2	47.4	31.1	100.0	91.1	62.9	64.3	37.8	41.7
Respect	Respect what has been promised	100.0	57.2	61.9	97.0	100.0	47.3	73.6	81.4	13.5
INTERACTIONAL FAIRNESS		**69.7**	**50.0**	**54.7**	**80.8**	**60.9**	**61.9**	**74.8**	**65.6**	**44.1**
Availability	Are kind and helpful	44.3	64.7	62.7	89.5	64.8	66.4	79.9	53.6	74.4
Personal needs	Are sensitive to personal and family needs	67.4	42.1	42.8	69.2	84.1	46.5	51.1	65.5	20.0
Working needs	Are sensitive to on-the-job needs	83.3	43.3	69.6	97.6	57.3	60.7	87.1	100.0	41.1
Listening	Pay attention to workers' ideas and proposals	48.7	48.8	64.7	45.3	84.4	82.3	79.0	52.1	27.0
Advices	Give advices and guidance	74.8	56.9	36.5	95.4	18.8	46.2	51.8	57.4	32.3
Attention	Give adequate weight to the quality of results	99.8	44.3	52.0	87.8	56.1	69.0	100.0	64.9	69.9
	VARIANCE EXPLAINED FROM ITEMS	**24.4%**	**19.3%**	**18.2%**	**48.1%**	**41.3%**	**38.4%**	**25.4%**	**19.1%**	**13.50%**

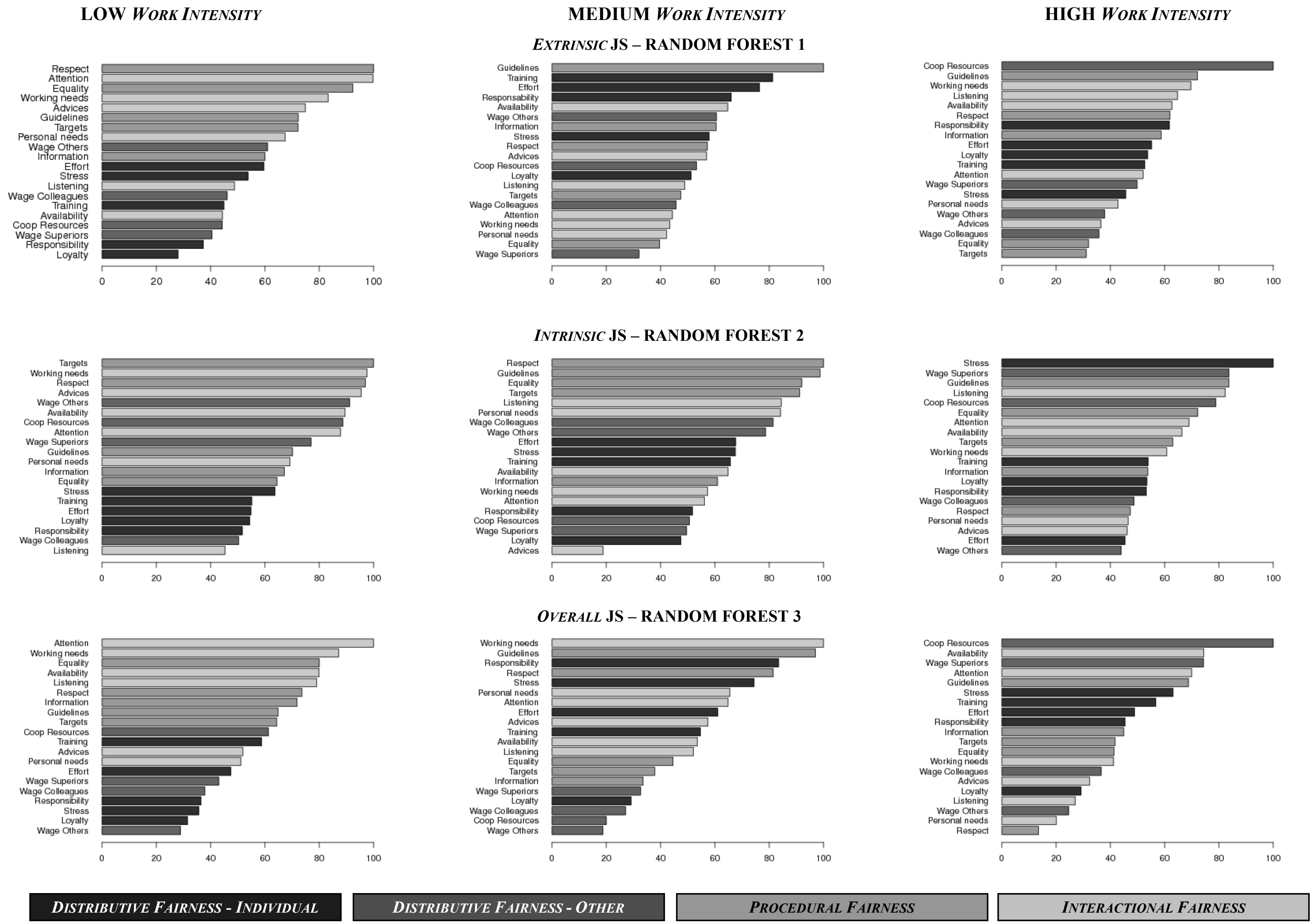

Figure 3. A graphical view of the MDA Variable Importance Indicator of the fairness drivers on JS for three different level of *WORK INTENSITY*.

4. Concluding remarks

In this study we use the Nonlinear Principal Component Analysis and the Rasch Rating Scale Model in order to construct two measures of JS (*INTRINSIC* and *EXTRINSIC*) and three measures of *WORK INTENSITY*, which are next used to classify the subjects within three homogeneous *WORK INTENSITY* clusters. In addition, for each cluster we run an algorithmic model (Random Forests) in order to evaluate the importance of fairness drivers on the different types of JS. We apply this methodology to the data coming from the Survey on the Italian Social Cooperatives ($ICSI^{2007}$).
The main findings from the $ICSI^{2007}$ sample are that the fairness drivers have different effect on JS, depending on *WORK INTENSITY*. For the group of workers with low *WORK INTENSITY* the *PROCEDURAL* and *INTERACTIONAL FAIRNESS* drivers have high importance on JS, while *DISTRIBUTIVE FAIRNESS* exhibits low importance. Instead, the workers in the medium *WORK INTENSITY* group seem to be focused on *PROCEDURAL FAIRNESS* and the workers in the high *WORK INTENSITY* group attribute a fundamental importance (as regards to JS) to the economic resources owned by the organization. Indeed, this last group of workers attributes high importance to two specific aspects of the fairness: when inspecting the *EXTRINSIC* and *OVERALL* JS, workers pay much attention to the cooperative resources; on the other hand, when *INTRINSIC* JS is explored, the stress on the job appears to be the most important variable. All these points to conclude that, firstly, non-monetary components of fairness play a key role in the JS and, secondly, the importance attributed to different fairness items varies depending on the grading of the *WORK INTENSITY*.

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Appendix

RESULTS CONCERNING THE WORK INTENSITY MEASURES

Table A1. Summary of the procedure for the 3 measures of the *WORK INTENSITY*
15 items for 3 subdimensions; GCA = 94; VAF = 41

Questions for the *WORK AUTONOMY*: **What is your agreement with the following statements?**
Response scale: 1 = "*Strongly disagree*", 2,…, 6, 7 = "*Strongly agree*".
Questions for the *WORK COMPLEXITY*: **Your work usually involves…**
Response scale: 1 = "*Definitely not*", 2,…, 4 = "*Neither no nor yes*",…, 6, 7 = "*Definitely yes*".
Questions for the *WORK RELATIONS*: **In your usual work, what time do you spend on relations with:**
Response scale: 1 = "*Never*", 2 = "*Rarely*", 3 = "*Sometimes*", 4 = "*Often*", 5 = "*Always*".

		Rotated NPCA			Rasch Analysis with RSM		
Measures and Items	***Descriptions***	***Loadings***			***Difficulty***	***Infit***	***Ptmea***
WORK AUTONOMY							
RA = 76; SM = 94; EV = 71							
Solve	I can solve for myself the problems that arise in my work	0.71	0.02	0.01	0.31	1.03	0.81
Manage	I can choose for myself how to manage my work	0.80	0.08	0.00	-0.14	0.89	0.82
Organize	I can choose for myself how to organize my work	0.73	0.02	0.08	-0.16	1.05	0.81
WORK COMPLEXITY							
RA = 79; SM = 95; EV = 75							
Decisions	Unexpected decisions in relations with users and their families	0.08	0.64	0.09	0.53	1.06	0.66
Goals	Goals difficult to achieve	0.01	0.74	0.06	0.45	0.84	0.69
Rates	High work rates	-0.04	0.58	0.09	0.23	1.01	0.64
Skills	Advanced skills	0.12	0.62	0.18	0.18	0.87	0.67
Activities	Involved simultaneously in very different activities	0.08	0.56	0.18	-0.05	1.17	0.63
Responsibility	Strong responsibility towards users and their families	-0.04	0.63	0.15	-0.34	1.17	0.66
Involvement	A continuous and intense involvement	0.01	0.50	0.20	-0.99	1.00	0.62
WORK RELATIONS							
RA = 72; SM = 98; EV = 75							
Volunteers	Volunteers	0.04	0.10	0.36	1.58	1.25	0.56
Others	Institutions and people outside the organization	0.14	0.27	0.40	0.67	1.08	0.60
Superiors	Superiors	0.06	0.05	0.61	-0.28	0.85	0.68
Team	Working group	-0.07	0.20	0.60	-0.62	1.12	0.69
Colleagues	Colleagues	-0.05	0.12	0.71	-1.35	0.73	0.70

Table A2. Descriptive statistics for the 3 measures of the *WORK INTENSITY*.

Measures	***Average***	***Std.Dev.***	***Coefficient of variation***	***Correlations***		
WORK AUTONOMY	0.35	1.52	4.34	1.00		
WORK COMPLEXITY	-0.08	0.65	8.13	0.02	1.00	
WORK RELATIONS	-0.13	1.02	7.85	0.06	0.32	1.00

Table A3. PCA results for the 3 measures of the *WORK INTENSITY* (VAF = 77).

	Component Matrix		Rotated Component Matrix	
Rasch Measures	***Comp1***	***Comp2***	***Comp1***	***Comp2***
WORK AUTONOMY	0.95	0.31	0.99	0.04
WORK COMPLEXITY	-0.16	0.79	0.05	0.81
WORK RELATIONS	-0.21	0.79	0.01	0.81

Table A4. Distribution of the 4,134 workers of the ICSI2007 for the two components of the *WORK INTENSITY*

Comp1 \ *Comp 2*	LOW	MEDIUM	HIGH	*Total*
LOW	277	492	265	1,034
MEDIUM	502	1,049	513	2,064
HIGH	255	524	257	1,036
Total	1,034	2,065	1,035	4,134

Table A5. Working characteristics and *WORK INTENSITY* of 3,614 workers of the ICSI^{2007} (%)

	WORK INTENSITY						
	LOW	**MEDIUM**	**HIGH**	**LOW**	**MEDIUM**	**HIGH**	*Total*
WORKER CHARACTERISTICS							
Gender							
Women	72.3	73.9	75.7	34.4	29.0	36.6	*100.0*
Men	27.7	26.1	24.3	37.4	29.1	33.5	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
Age							
18-30	21.3	24.6	20.2	34.3	32.6	33.1	*100.0*
31-49	64.1	65.3	67.6	34.3	28.8	36.8	*100.0*
50-74	14.6	10.1	12.1	41.3	23.7	35.0	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
Education							
Secondary-school diploma	45.8	28.9	26.7	47.3	24.6	28.0	*100.0*
High-school diploma	34.9	37.1	36.2	34.1	29.9	36.0	*100.0*
Graduate	19.4	34.0	37.1	22.7	33.0	44.3	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
WORK CHARACTERISTICS							
Membership							
Member	71.8	75.2	79.7	33.4	28.9	37.7	*100.0*
Non-member	28.2	24.8	20.3	40.6	29.5	29.9	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
Activity area							
Service delivery area	64.2	64.0	53.1	37.5	30.9	31.6	*100.0*
No service delivery area	25.2	20.4	24.6	37.6	25.1	37.3	*100.0*
Multi-area	10.6	15.6	22.3	23.0	27.9	49.1	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
Contract type							
Permanent contract	77.7	80.6	83.5	33.9	29.0	37.1	*100.0*
Self-employment, atypical contracts	22.3	19.4	16.5	40.5	29.1	30.5	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
Working time regime							
Full-time	50.2	54.3	63.2	31.5	28.1	40.4	*100.0*
Volunteer part-time	35.1	33.6	27.6	38.6	30.5	30.9	*100.0*
Forced part-time	14.7	12.1	9.2	43.2	29.3	27.5	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
COOPERATIVE CHARACTERISTICS							
Activity type							
Type A	71.4	82.6	81.8	32.1	30.6	37.4	*100.0*
Type B	28.6	17.4	18.2	46.5	23.4	30.1	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*
Geographical location							
North-West	39.9	40.1	41.9	34.5	28.6	36.9	*100.0*
North-East	22.6	18.8	22.0	37.3	25.6	37.1	*100.0*
Centre	23.1	22.8	20.1	37.0	30.2	32.8	*100.0*
South and Islands	14.5	18.3	16.0	31.6	32.9	35.5	*100.0*
Total	*100.0*	*100.0*	*100.0*	*35.2*	*29.0*	*35.8*	*100.0*