

**Matilde Bini, Pietro Amenta, Antonello D'Ambra, Ida Camminatiello**  
*Editors*



# Statistical Methods for Service Quality Evaluation

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# Statistical Methods for Service Quality Evaluation

## **Book of short papers**

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## Diagnostic tools for Ordered Logit Models in an analysis of relationships between Public Service Motivation and Individual Performance

Anna Crisci, Luigi D'Ambra, Raffaella Palma

### Abstract

Many studies find positive associations between public service motivation (PSM) and performance, but much of this literature is based on specific quantitative methodology. Moreover, we know little about in which order the motives underlying the PSM impact on individual performance. In this study, we analyze the relationship between PSM and individual performance through regression models with ordinal response variable. Moreover, we consider the surrogate approach to constructing residuals in order to check the assumption in Ordered Logit Model.

**Key words:** Public Service Motivation, Ordered Logit Model, Brant test, Simplot, Surrogate residual

### Introduction

Public employees go above and beyond the call of duty and perform well (Dilulio, 1994). One explanation seems to be rooted in public service motivation (PSM), which drives employees in organizations or jobs with a public function to perform well (Brewer, 2006). PSM consists of four dimensions: Attraction to Policy Making (APM), Commitment to Public Interest (CPI), Compassion (C), Self-Sacrifice (SS). Much research shows that employee PSM is a determinant of performance in public organizations (Vandenabeele, 2009; Warren & Chen, 2013). However, more research that expands our understanding of the PSM–performance relationship is needed. In this paper, we investigate the association between teacher PSM and their perceived performance by means of regression models for ordinal outcomes. Moreover, in order to check the assumption in Ordered Logit Model we consider the diagnostic tools based on residuals. For a continuous outcome, the residual is traditionally defined as the difference between the observed and fitted values. For ordinal outcomes, the residuals are more difficult to define. Liu et al. (2009) propose using the cumulative sums of residuals

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derived from collapsing the ordered categories into multiple binary outcomes. Unfortunately, this method leads to multiple residuals. For ordinal outcomes Li and Shepherd (2012) proposed the sign-based statistic (SBS). Finally, we examined the surrogate residuals (Liu and Zhang, 2017), by considering a continuous variable based on conditional distribution of a latent variable.

## 2. Ordered logit Models (OLM)

Techniques such as ordinary Least Squares Regression require that outcome variables have interval or ratio level measurement. When the outcome variable is ordinal, other types of methods should be used. The most popular method is the ordered logit model, which is also known as proportional odds model (PO). Let  $Y_i$  be an ordinal response variable with  $J$  categories for  $i$ -th subject ( $i=1\dots n$ ), alongside with a vector of covariates  $\mathbf{x}_i$ . The  $Y_i$  are statistically independent. We define  $g_{ij} = \Pr(Y_i \leq y_j | \mathbf{x}_i)$  as the cumulative probabilities for  $j = 1, \dots, J - 1$ . The cumulative probabilities are related to a linear predictor  $\mathbf{x}'\boldsymbol{\beta}$ , through the logit function:

$$\text{logit}(g_{ij}) = \ln\left(\frac{g_{ij}}{1-g_{ij}}\right) = \alpha_j - \mathbf{x}_i'\boldsymbol{\beta}, \quad j = 1, 2, \dots, J - 1$$

The parameter  $\alpha_j$ , called thresholds or cut-points, are increasing order  $\alpha_1 \leq \alpha_2 \dots \leq \alpha_{J-1}$ .  $\boldsymbol{\beta}$  is the regression parameter vector of  $\mathbf{x}$  and shown as  $\boldsymbol{\beta} = (\beta_1 \dots \beta_k)$ . In ordinal logistic regression models, there is an important assumption which belongs to ordinal odds. According to this assumption parameters should not change for different categories. In an ordinal logit regression, when the assumption holds for  $J - 1$  logit comparison in a  $J$  categorized variable,  $\alpha_{j-1}$  thresholds points and  $J - 1$  parameters are found. In a way, this assumption states that the dependent variable's categories are parallel to each other. When the assumption does not hold, Likelihood Ratio Test, Wald Chi-Square test, Brant test, Wolfe Gould test and the other related tests are used to test parallel lines assumption (Long, 1997; Agresti, 2002).

### Case study

In this section, we investigate the association between teacher PSM and their perceived performance only by considering the Proportional odds model

(POM). The independent variables considered are the three of the four dimensions of PSM (CPI, C, and SS). In the analysis, the more relevant items are as follows: CPI1 “It is hard for me to get intensely interested in what going on in my community”, CPI2 “I unselfishly contribute to my community”; CPI3 “Meaningful public service is very important for me”; CPI4 “I would prefer seeing public officials do what is best for the whole community even if it harmed my interests”; CPI5 “I consider public service my civic duty”; SS1 “Making a difference in society means more to me than personal achievements”; SS2 “I believe in putting duty before self”; SS7” I am one of those rare people who would risk personal loss to help someone else”; SS8”I am prepared to make enormous sacrifices for the good of society”; C1 “I am rarely moved by the plight of the underprivileged”, C2 “Most social programs are too vital to do without”, C3 “It is difficult for me to contain my feelings when I see people in distress”; C4 “To me, patriotism includes seeing to the welfare of others”; C5 “I seldom think about the welfare of people whom I don’t know personally”. In table 1, we show only the result of POM with all predictor variables was fitted. The log likelihood ratio Chi-square test, LR  $\chi^2(11) = 133,92$ , Prob >  $\chi^2 = 0.0000$ , indicating that the full model with all predictor a better fit than the null model with no independent variables.

**Table 1:** Ordered logit model

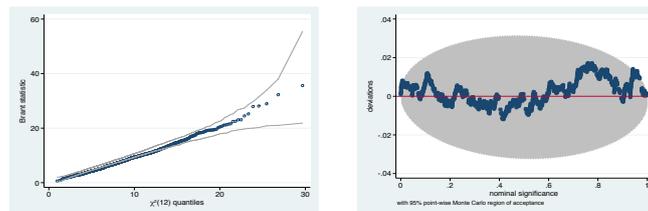
Performance	Odds	Std. Err.	z	p-value
CPI1	1.130	0.127	1.09	0,275
CPI2	1.150	0.139	1.16	0,244
CPI3	1.146	0.138	1.13	0,258
CPI4	1.105	0.117	0.95	0,341
CPI5	0.896	0.082	-1.19	0,235
SS1	1.017	0.093	0.19	0,850
SS2	1.338	0.147	2.65	0,008**
SS7	1.069	0.118	0.60	0,546
SS8	1.477	0.165	3.49	0,000**
C1	0.798	0.093	-1.94	0,052
C2	1.043	0.115	0.38	0,702
C3	1.435	0.162	3.18	0,001**
C4	1.102	0.120	0.89	0,372
C5	0.974	0.112	-0.23	0,822
/cut1	2.088	0.318		
/cut2	5.382	0.376		
/cut3	7.780	0.486		
/cut4	9.114	0.694		

(\*\*significant at 5%)

In order to reduce the complexity of model we following the stepwise procedure. In particular, we randomly divide your sample into two sub-sample. We use the first sub-sample as the exploration sample, in which the stepwise are performed in order to choice your model. Later, we verify the fit of this model with the second sub-sample. In our case, the result are very similar, then our model reflects the underlying process. The stepwise results

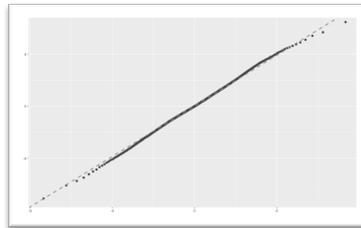
shown that the most important and significant ( $p < 0.05$ ) variables are C3, SS8, CPI2, SS2. To test the PO assumptions, the Brant test provided the results for the overall model and each predictor. The Brant test for the model,  $\chi^2 = 14,32$ , p.value = 0, 281, indicating that the parallel line assumption are met.

To verify if Brant test well perform, we use a simplot that describe the results of a simulation that inspect the coverage of a statistical test. Simplot describe by default the deviations from the nominal significance level against the entire range of possible nominal significant levels. It also shows the range (Monte Carlo region of acceptance) within which one can reasonably expect these deviation to remain if the test well perform. In our case, the Brant test is well behaved (Figure 1)



**Figure 1:** Simplot Brant test

Moreover, in order to assess the goodness of fit of ordinal logistic models we performed a Generalized Hosmer-Lemeshow test. This test compares observed with expected frequencies of the outcome and computes a test statistic which is distributed according to the chi-squared distribution. In our case, the chi-square = 44.68,  $df = 31$ , p-value = 0.05322. We have a non-significant p value, that is, there is no evidence that the observed and expected frequencies differ (i.e., evidence of good fit). Finally, to check assumptions in the ordinal regression model (i.e. misspecification mean structure, proportional, heteroscedasticity, etc.) we will use a more recent approach based on surrogate residuals which produce diagnostic plots not unlike those seen in ordinary linear regression. The Q-Q plots in Figure 2 does not show a deviations from the hypothesized model, then, the logit link is appropriate.



**Figure 2:** Q-Q plots of the residuals for model with logit link.

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